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Testing weak form market efficiency with technical analysis

Finance
Master´s Thesis
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Spring 2004

Approved by the Council of the Department 7 / 9 2004 and awarded the grade good 70 points

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ABSTRACT
23.7.2004

TESTING WEAK FORM MARKET EFFICIENCY WITH TECHNICAL ANALYSIS

Objectives of the study

The purpose of this study is to examine the market efficiency of Budapest (BSE), Prague (PSE) and Warsaw Stock Exchange (WSE) with technical analysis. Simultaneously the research evaluates the profitability of technical analysis and how the assumptions applied in the methodology affect the research results.

Data

The survey employs market data from three selected stock exchanges. This means daily close values of 3 major indices and 13 shares with highest liquidity and market capitalization.

Methodology

According to the theory of market efficiency, systematic trading should not bring profits higher than the ones gained with buy & hold strategy. To evaluate the possibilities of active trading, the research is started with statistical methods appropriate for testing the random walk hypothesis and conditions for successful technical analysis. This means assessments of stationarity and autocorrelation that are completed with runs tests. After this the selected trading strategies are applied to all 16 original share and index series, but also to 5 different portfolios constructed with the original series. The applied technical trading strategies are moving average (MA) and relative strength index (RSI) rules.

Results

The results proved only three of the explored time series to be stationary. However, further statistical testing revealed all stock markets to have characteristics typical for an inefficient market. Even after employing the tests for differenced and residual data, twelve out of sixteen series seemed to contain significant autocorrelation. Also runs tests proved that eight out of the sixteen series include runs that can't have occurred by chance alone. The results indicated at least some of the markets to be suitable for successful technical analysis. This was supported by the first trading results, where out of all trading simulations 39% provided abnormal profits. However, trading profitability varied considerably between different time series. Although the results indicated that some of the series and even the whole Poland market did not follow the random walk hypothesis, further research was required as the results were very sensitive to changes in trading environments. When evaluating how the assumptions applied in the methodology affect the research results, the amounts of profitable series and the profit levels were proved to vary considerably, especially with different trading costs. With previously reported average emerging market costs, the abnormal profits were gained only in noticeably rare cases. Consequently, the study suggests that in these markets average investors can't have used active trading to gain abnormal profits and the conditions of weak form market efficiency are met.

Keywords

Market efficiency, Technical analysis, Moving average, Relative Strength Index, RSI

HELSINGIN KAUPPAKORKEAKOULU
Rahoituksen tutkielma
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23.7.2004

MARKKINATEHOKKUDEN HEIKKOJEN EHTOJEN TOTEUTUMISEN TESTAAMINEN TEKNISEN ANALYYSIN AVULLA

Tutkimuksen tavoitteet

Tutkimuksessa tarkastellaan teknisen analyysin avulla osakemarkkinoiden heikkojen ehtojen toteutumista Budapestin (BSE), Prahan (PSE) ja Varsovan (WSE) pörssien pääomamarkkinoilla. Samalla työssä arvioidaan teknisen analyysin tuottavuutta ja selvitetään tutkimusmenetelmässä käytettyjen oletusten vaikutusta tutkimustuloksiin.

Lähdeaineisto

Aineistona käytetään osakkeiden ja markkinaindeksien päivittäisiä päätöskursseja. Mukana on kyseisten pörssien 13 likvideintä ja markkina-arvoltaan suurinta osaketta sekä 3 indeksiä.

Aineiston käsittely

Markkinatehokkuutta koskevan teorian mukaisesti tehokkailla markkinoilla ei systemaattisilla kaupankäynnillä voida saavuttaa osta ja pidä -strategiaa korkeampia tuottoja. Niinpä työssä tutkitaan, voidaanko valituilla kaupankäyntistrategioilla saavuttaa tällaisia ns. ylisuuria voittoja 16 alkuperäisen osake- ja indeksisarjan sekä näistä muodostetun 5 erilaisen portfolion kohdalla. Tutkimuksessa sovellettavat kaupankäyntistrategiat perustuvat teknisen analyysin menetelmiin, jotka ovat liukuva keskiarvo (MA) ja suhteellinen voimaindeksi (RSI). Lisäksi valittujen aikasarjojen satunnaisuutta ja soveltuvuutta menneeseen markkinainformaatioon perustuvaan kaupankäyntiin arvioidaan tilastollisen tarkastelun eli stationaarisuuden, autokorrelaatioiden ja runs-testien avulla.

Tulokset

Tutkimuksen mukaan vain kolme alkuperäisistä osake- ja indeksisarjoista on stationaarisia. Tästä huolimatta tilastollinen tarkastelu paljasti tehottomille markkinoille ominaisia piirteitä, sillä merkittävää autokorrelaatiota havaittiin kuudestatoista tutkittavasta aikasarjasta jopa viidellätoista. Edelleen runs-testit osoittivat näistä kahdeksan käyttäytyvän sattumasta poiketen. Ensimmäisten tulosten perusteella edellytykset onnistuneelle tekniselle analyysille olivat olemassa ja 39 prosentilla kaupankäyntisimulaatioista voitiinkin saavuttaa osta ja pidä -strategiaa suurempia ns. ylisuuria tuottoja. Analyysin toimivuus kuitenkin vaihteli suuresti aikasarjasta riippuen. Tulokset osoittavat tiettyjen sarjojen ja Puolan kohdalla jopa kokonaisten markkinoiden keskimääräisen markkinakehityksen poikkeavan random walk -oletuksesta ja että autokorrelaatiota pystytään käytännössä hyödyntämään. Kuitenkin arvioitaessa tutkimusmenetelmässä käytettyjen oletusten vaikutusta tuloksiin, havaittiin tuottoisten sarjojen määrän ja tuottojen suuruuden vaihtelevan etenkin kaupankäyntikustannusten vaikutuksesta. Ylisuurien voittojen tekeminen keskimääräisiä kasvavilla pääomamarkkinoilla havaittuja kaupankäyntikustannuksia vastaavien kustannusten jälkeen onnistui huomattavasti harvemmissa tapauksissa, mikä osoittaa markkinatehokkuuden heikkojen ehtojen toteutuvan kaikilla valituilla markkinoilla.

Avainsanat

Markkinatehokkuus, Tekninen analyysi, Liukuva keskiarvo, Suhteellinen voimaindeksi, RSI

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1 INTRODUCTION

1.1 Background

According to the theory of efficient market, in an efficient capital market all relevant information concerning each company's prospects is already reflected in price levels. As all the market participants access this information and agree on the correct price level, further information processing does not profit an individual investor. In other words, no analysis method or active trading strategy should provide higher profits than what the investors may gain on average.

However, this condition applies only to *strong* form market efficiency as the definition of relevant information differs according to the form of market efficiency. The relevant information set can be considered to include all *historical*, *published* or *available* information depending on the respective form of market efficiency i.e. whether markets are *weak*, *semi-strong* or *strong* form efficient.

The weaker the market efficiency is, the more profitable forecasting methods there may exist, also theoretically. Therefore, the investors are provided a wide variety of different tools for making abnormal profits. Roughly these different forecasting methods can be divided to two main categories - *fundamental analysis* and *technical analysis*. In general, the methods in both classes try to reveal the correct price levels with certain variables calculated with various sources of information, while the main difference of these categories is in this information employed and, consequently, in the assumptions of current market efficiency.

Fundamental analysis assumes the market to be at least weak form efficient. The focus is in the latest data while the historical data is considered as irrelevant. In more detail, the analysis focuses on new published information that includes e.g. financial information of individual companies, business sectors or markets. The calculated variables include company profitability, solidity, growth, market potential or different economy indicators etc. For investors the analysis provides figures that can be interpreted to trading signals with rather subjective criteria.

Technical analysis ignores the whole efficient market hypothesis. The basic idea is to search and forecast repeated and predictable patterns with historical data e.g. stock prices and volumes that are assumed to be affected by economical, political and psychological factors. For investors technical analysis usually means the use of indicators that provide direct signals for trading.

Fundamental analysis, therefore, does not support assumptions behind technical analysis while technical analysis finds fundamental analysis too thorough. While the fundamental analysis can be defined to be interested in the reasons of the changes in the market, technical analysis concentrates on the results. In other words, technical analysts are interested in the question how the previous market behavior affects the prices, but ignore the reasons.

Bodie et al. (1999) have concluded that, although technicians recognize the value of information regarding future economic prospects of the firm, they believe that such information is not necessary for a successful trading strategy. This is because whatever the fundamental reason for a change in stock price, if the stock price responds slowly enough, the analyst will be able to identify a trend that can be exploited during the adjustment period. The key to successful technical analysis is a sluggish response of stock prices to fundamental supply-and-demand factors.

The methods are even sometimes seen as complementary tools. According to one approach, fundamental analysis has been recommended for long-term investment decisions following buy & hold[1] strategy while technical analysis is ideal for investors relying on short-term trading. It has been also stated that they are often even used together. The fundamental analysis is used to select the companies that are healthy and appear as promising investments. Technical analysis is then used to find the correct timing for buy and sell decisions.

Although the major difference between these two methods lies in the assumption of the form of market efficiency and the method success depends on prevailing efficiency, technical analysis value has been often questioned. Markets have been regarded as at least weak form efficient and the discussion has focused on semi-strong and strong form efficiencies, when technical analysis is considered to be worthless.

However, both analyses are popular. The wide used use of technical analysis has been also proved in previous studies. For example Brown & Jennings (1989) demonstrated that rational investors use historical prices in forming their demands. Also Taylor (1992) conducted a survey including major foreign exchange dealers based in London and found that in excess of 90% of respondents placed some weight on technical analysis when predicting future returns. Even more recently, Sullivan et

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[1] In buy & hold strategy money is invested on the first day of the period. The shares etc. are sold on the last day of the period. There exists no other trading.

al. (1999) concluded that after more than a century of experience with technical trading rules, these rules were still widely used to forecast asset prices.

Sullivan et al. (1999) assumed that the wide use of technical analysis in the finance industry has forced several academics to determine its value and, consequently, also weak form market efficiency has been regularly examined. Some of the researches have employed statistical methods, but especially most recent studies have focused on estimating the profitability of technical analysis. As the form of market efficiency defines the success of technical analysis, the success of technical analysis has been now used to estimate the form of current market efficiency.

Although the studies have used the data from same markets, due to the different methodologies, the results have differed considerably. As the study results vary, the information is interpreted and concluded in many different ways. Consequently, still relatively little is known regarding the efficiency of different markets. However, what has been often agreed is the fact that market inefficiencies are estimated to change over time. It has been stated that the markets have become more efficient in developed countries, while the younger emerging markets are supposed to still be more predictable. This indicates that, in addition to conditions favoring fundamental analysis, some inefficient markets may provide also conditions suitable for profitable technical analysis.

1.2 Research Objectives and Scope

The purpose of this study is to examine the weak form market efficiency and technical analysis profitability in the emerging East European capital markets. The selected markets include Budapest Stock Exchange (BSE), Prague Stock Exchange (PSE) and Warsaw Stock Exchange (WSE).

The main contribution of this research lies in applying the methods, used mainly in US and other developed markets, in less developed and less researched East European markets. First the research employs different statistical methods to test time series randomness and preconditions for profitable technical analysis. In addition to common runs tests, the statistical analysis means evaluation of stationarity and autocorrelation of all applied series.

The market efficiency is then tested by evaluating the success of technical analysis i.e. by estimating whether applying trading strategies to selected equities, indices and portfolios produces profits higher than the ones gained with buy & hold strategy. If a market does not meet the conditions of weak form market efficiency, systematic trading may bring abnormal profits.

The applied technical trading strategies are Moving Average (MA) and Relative Strength Index (RSI). These methods are meant for markets with opposite characteristics, which has also acted as the main rationale for method selection. Further, the moving average method is considered to be a reliable and simple method for trending time series. However, if there is no clear trend in the market, the employed method should be one of the trading-range ones, such as RSI. Additionally, as the simultaneous use of two different types of strategies has been often recommended, also combinations of these rules have been applied.

The data consists of shares and a major index from each market. The shares represent different business sectors while the summed capitalization or annual volume of the shares represents 50% of the total capitalization or volume of each market. Due to low overall liquidity, only 4-5 major shares from each market are needed to meet these requirements. The shares from a single market are used to construct a country-specific portfolio. In addition to these 3 country-specific portfolios, a total portfolio including all 13 shares and an index portfolio with all 3 indices are formed.

As the previous study results have varied considerably, this study also evaluates how the methodology variations affect the research results. These variations include different trading costs, trading rules, trading bands, secondary investments, trading periods and performance indicators.

Additionally, based on previous studies, econometric modeling literature, theory of market efficiency and technical analysis literature, this study aims to provide a comparison of popular methodologies used for market efficiency evaluation. The purpose of this review is to provide a rationale for methodology selection, to be applied possibly also in future studies.

Due to the wide variety of different trading methods, this research concentrates on describing and comparing the simple and most common trading methods that are applied also in previous studies or recommended often in technical analysis literature. Therefore several common analysis methods have been excluded. For example, volume analysis has been used and researched frequently, but excluded completely from this study.

Also seasonalities and their relationship to market efficiency have been researched frequently. Although these researches have been mentioned in chapter 2 summarizing previous researches, closer description is excluded in this paper. Like stated in chapter 3.4.1, seasonality is considered here as a subject only closely related to weak form efficiency.

1.3 Structure of the Study

The remainder of this study is organized as follows. Chapter 2 reviews the previous research on market efficiency and usefulness of technical trading rules in developed and developing countries. Chapter 3 describes the efficient market theories including the main motivation for the research. Chapter 4 illustrates the assumptions and basics of technical analysis. Chapter 5 contains classifications and explanations of the most common simple trading rules. Chapter 6 focuses finally on the use, interpretation and selection of the methodology applied in this study. In addition to the trading rules, the statistical tests applied in this study are described. This chapter describes also the measures used for trading performance evaluation. Emerging markets, the selected stock exchanges and time series data used in the study are described in chapter 7. The empirical research results are described in chapter 8 that begins with the time series stationarity, autocorrelation and runs tests. Before trading simulations, the buy & hold strategy success is evaluated. After this the trading rules are applied and the mechanical trading profits are compared to the profits gained with buy & hold strategy. Concluding remarks are offered in chapter 9.

The structure of the study is illustrated in the figure 1 below. This shows the main steps and the connections between these.

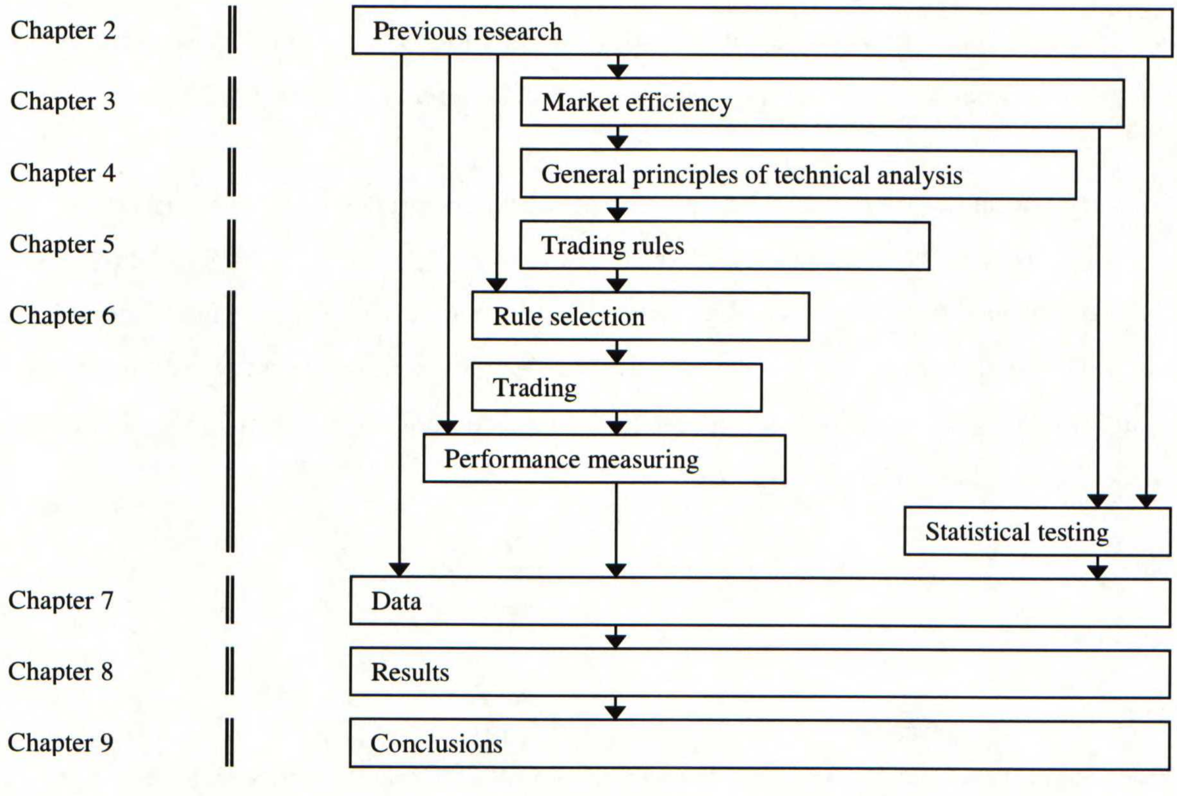

Figure 1 Structure of the study

2 PREVIOUS RESEARCH

The previous researches exploring the market efficiency are various. Most of them are concerned whether prices "fully reflect" particular subsets of available information. In the ones evaluating the weak form efficiency[2], the information subsets of interest are usually past price or return histories. In practice the research has been implemented by checking certain seasonalities[3] or time series patterns by employing different statistical and technical trading methods. The technical methods have mainly simulated active trading where buy and sell decisions have been based on simple rules such as moving averages, filters and relative strength indices. The researches employing statistical methods have analyzed autocorrelations, runs, autoregressive integrated moving averages (ARIMA) econometric regression models etc.

Naturally the developed markets have been researched in greater extent as they present older market places with longer sets of time series data. However, for some years studies have concentrated also in the emerging markets.

This chapter summarizes the previous researches testing the weak form efficiency with statistical testing or mechanical trading simulation. The summary focuses on the most well-known researches, referred also in the most recent papers, and on the ones evaluating efficiencies of emerging markets. However, due to great number of different studies, many researches could not be presented. For example, this summary excludes all previous researches surveying volume data.

Before concentrating on the more recent researches, the early researches will be described. As the studies including US data have been carried out most frequently, both earlier and more recent studies have been divided also to researches with US data and researches containing data from other markets. The main interest lies in the chapter 2.2.2 describing more recent researches mainly with emerging market data. This study is closest to the research employed by Isakov & Hollistein (1999) that can be found as the last one on the list.

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[2] Market efficiencies, their characteristics and classifications together with the exemplary ways to evaluate these will be described in more detail in the chapter 3.

[3] As mentioned in chapter 3.4.1, according to Berglund (1986), seasonality is a subject only closely related to weak form market efficiency. Therefore seasonalities will be ignored after the chapter 2.

2.1 Early Studies

2.1.1 US Studies

The random walk[4] model was originally examined by Kendall (1953) with UK data, but Roberts (1959) implemented a similar, though less comprehensive, work with American data. This was one of the first studies estimating random walk and market efficiency of capital markets. The study was implemented with *chance model*[5]. After employing the methodology to index and individual company data, the model rejected the possibility to benefit from price movements on the longer run. There was no commitment about the relative frequencies of different outcomes, except that these must be stable over time. Roberts presented evidence supporting the weak form market efficiency.

Alexander (1961) formulated *filter technique*[6] to test the belief, that prices adjust gradually to new information. He was the first to confirm the profitability of technical trading with individual US stocks. According to the study, the price changes seemed to follow a random walk over time, but a move, once initiated, tended to persist. Because of imperfect knowledge, new information generated trends rather than instantaneous jumps.

Later, Alexander (1964) reworked his earlier results to take into account the source of bias that caused serious overstatement of profitability. He finally found that profitability disappeared once trading costs were introduced.

Fama (1965) researched New York Stock Exchange efficiency with 30 stocks. He surveyed *the price change distributions, serial correlations, runs*[7] and finally applied Alexander's (1961) *filter technique*. He presented strong evidence favoring the random-walk hypothesis and found no evidence that stock prices contained any dependence that could be regarded as important for investment purposes.

Fama & Blume (1966) applied *filter techniques* similar to the ones used by Alexander and confirmed that technical trading rules could not be used successfully in the US equity markets when trading costs were considered.

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[4] Random walk model will be described in more detail in chapter 3.2.2.
[5] Chance model is basically a simple mechanical device that should duplicate many of the features of stock-market movements like serial correlations and cross-correlations.
[6] Filter technique will be described in more detail in chapter 5.4.
[7] Runs test will be described in more detail in chapter 6.3.3.

Levy (1967a, b) surveyed variations of a technical trading rule called *relative strength*[8] or *portfolio upgrading* rule. His results indicated that on US markets some variations of the applied trading rules performed substantially better than simple buy & hold strategy.

Jensen & Benington (1970) reported the results of an extensive set of tests employing two Levy's rules. They applied the rules on 29 independent samples of 200 securities. After allowance for transaction costs, the rules did not, on average, earn abnormal profits on US equity markets. Additionally, they also surveyed risk in the form of portfolio *standard deviation.* Since the average trading rule portfolios were more risky than the buy & hold portfolios, they suggested that this simple comparison of returns was biased in the cases favoring active trading.

2.1.2 Other Markets

The early research by Kendall (1953) proved the English stock market to follow the random walk hypothesis. He calculated the first 29 lagged serial correlations of the first differences of 22 time series representing speculative prices. After examining data with the *chance model* he finally could find no predictable patterns in stock prices. He suggested that the changes in security prices behaved nearly as if they had been generated by a suitably designed roulette wheel for which each outcome was statistically independent of history and for which relative frequencies were reasonably stale through time. Prices seemed to evolve randomly.

Solnik (1973) surveyed eight European i.e. French, West German, Italian, Dutch, Belgian, English, Swiss and Swedish stock markets. He studied the *distribution* and *stationarity* of *serial correlation coefficients* of individual securities. The results proved the markets to follow random walk and to be weak form efficient. However, the results differed slightly from those found in US. They indicated lesser efficiency in most European stock markets.

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[8] Relative strength of a stock is indicated by a ratio comparing the stock price to an appropriate index. It should be noticed that relative strength rule is different from relative strength index rule used also in this study.

2.2 More Recent Studies

2.2.1 US Studies

Recent evidence indicates that some technical trading rules may have had the ability to forecast price changes in the US equity markets. Sweeney (1988) developed a test of statistical significance of *filter rule* profits and re-examined the results of Fama & Blume (1966). He showed that similar filter rules could produce excess profits depending on the level of transaction costs.

Lo & MacKinlay (1988) tested the random walk hypothesis with weekly US stock market returns by comparing *variance estimators* derived from data sampled at different frequencies. The empirical results indicated that the random walk model was generally not consistent with the stochastic behavior of weekly returns, especially for the smaller capitalization stocks. In more detail, they found significant positive serial correlation for weekly and monthly holding period returns. Consequently, the random walk model was strongly rejected for the entire sample period 1962-1985 and for all subperiods. This is actually in contrast to the results that Fama & French (1987) found when they examined the connection between stock returns and stock market volatility. They found negative serial correlation for longer-horizon returns.

Also Jegadeesh (1990) examined the *serial correlation* properties of returns of individual securities. The paper documented strong evidence for predictable behavior of security returns. The results show that the monthly returns of individual stocks contained significant negative first-order serial correlation and significant positive high-order serial correlation. In practice, a portfolio consisting of extreme losers within a month tended to earn about 2% above the average in the following month. Consequently, the results rejected the hypothesis that the stock prices follow random walk. The author concluded that the predictability of stock returns could be attributed either to market inefficiency or just to systematic changes in expected stock returns.

Brock et al. (1992) demonstrated profitable *moving average*[9] and *trading-range break*, also known as *resistance and support*[10], trading rules using Dow Jones Industrial Average (DJIA) from 1897 to 1986. Standard analysis is extended with *bootstrap techniques*[11] to estimate the compatibility and

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[9] Moving average trading rules will be discussed starting from chapter 5.5.

[10] Trading-range break i.e. support and resistance trading rules will be discussed in chapter 5.3.2.

[11] The bootstrap method has been applied in finance studies for a wide variety of purposes. The bootstrap method can be used e.g. to generate many different series by sampling with replacement from the original series. The samples are pseudo series that retain all the distributional properties of the original series, but are purged of any serial dependence.

dependencies of different methods and, further, to eliminate the problems caused by distributions that are not normal, stationary and time independent. After extensive testing, the research still suggested the previous researches to be overpessimistic. Although bootstrap methodology was employed, the study revealed that significant profits could be gained with historical data, even with transaction costs. Brock et al. study has been repeated several times with little variations in the methodology and with different data as can be seen below.

Ready (1997), using intraday US data, found that the Brock et al. trading rules do not beat buy & hold strategy due to trading costs and the time it takes to execute the actual trade. The trading rules were now applied to more recent data, from the period 1990-1995. There was also a decline in the ability of technical trading rules to predict daily returns. The decreased profit opportunities were explained with improved market efficiency.

To avoid the dangers of data-snooping, also Bessembinder & Chan (1998) evaluated precisely the same set of trading rules as Brock et al. (1992). Also they suggested that the inclusion of reasonable trading costs and the adjustments for non-synchronous trading eliminated the profitability of technical trading. Although they didn't question the economic significance of the Brock et al. study, they argued that the evidence of technical forecast power doesn't need be inconsistent with market efficiency. Bessembinder & Chan researched and reported also the break-even transaction costs for Brock et al. (1992) study. Break-even trading costs were quite small, averaging 0.39% for the full 1926 to 1991 sample. When the total data was divided to smaller subperiods, they found that break-even costs declined over time, from 0.54% in the first subperiod to 0.22% in the last. According to the study, these estimated trading costs are similar or smaller than the recent estimates of actual trading costs, implying that during the sample period traders likely could not have used this set of technical trading rules to improve returns net of trading costs.

Sullivan et al. (1999) utilized White's reality check *bootstrap methodology* to evaluate *simple technical trading rules*. They considered the study of Brock et al. (1992), expanded the universe of 26 trading rules, applied the rules to 100 years of daily data on the Dow Jones Industrial Average, and determined the effects of data-snooping. According to Sullivan et al., historically the best trading rule possibly did produce superior performance. However, as stated also by Ready (1997), the markets have become more efficient and such opportunities have disappeared.

2.2.2 Other Markets

Also the evidence of *seasonalities* in different markets, including US stock market, is plentiful. For example, Cadsby & Ratner (1992) studied both *turn-of-month* and *pre-holiday effects* in ten different stock markets. There existed evidence for both effects in several markets.

Aggarwal & Rivoli (1989) analyzed the *seasonal* and *day-of-the-week effects* in four emerging stock markets. Agrawal & Tandon (1994) examined five *seasonal patterns* in stock markets of eighteen countries. Again, also emerging markets were included. Both researches identified seasonalities in emerging markets.

Harvey (1995a) studied a conditional asset pricing model with data from 20 new equity markets in emerging economies. He reported that stock returns of emerging countries are highly predictable and have low correlation with stock returns of developed countries. He concluded that emerging markets are less efficient than developed markets and that higher returns and lower risk can be obtained by incorporating emerging market stocks in portfolios.

The profitability of technical trading rules in emerging markets has also been associated with the persistence of returns, or autocorrelation, in these markets. Harvey (1995b) found that *autocorrelation* in emerging markets was much higher than in developed markets. He also suggested that the level of autocorrelation is directly associated with the size and concentration of the market.

Claessens et al. (1995) conducted tests of market efficiency for 20 emerging countries using stock indices and portfolios of different sizes. Random walk was rejected in many cases as they reported significant *autocorrelation* for half of the countries. Additionally, their *variance-ratio tests* rejected the random walk for seven countries.

Urrutia (1995) used *variance-ratio tests* and *runs tests* to investigate random walk and weak form market efficiency in four Latin American emerging markets. He finally rejected the random walk hypothesis, which indicated potentially exploitable inefficiencies. However, the empirical findings suggested that trading strategies can't have provided excess returns and therefore weak form efficiency could not be rejected.

Bessembinder & Chan (1995) evaluated again the performance of precisely the same set of 26 technical rules as Brock et al. (1992) in several Asian markets. They found that the trading rules could be profitable in some Asian countries. However, they surveyed also the break-even trading costs and noticed that only considerably low trading costs enabled actual abnormal profits.

Also *risk factors* have been used as explanatory variables. Harvey (1995c) addressed predictability by utilizing a pricing model. He contended that emerging market returns seemed to be predictable when using international and local risk factors. Erb et al. (1996) found that equity returns and volatility were predictable for 48 countries by using *credit risks,* obtained from a publication called *Institutional Investor,* as the sole explanatory variable. Additionally, according to Diamonte et al. (1996), *political risk measures* could predict the returns in emerging markets better that in developed markets.

Hudson et al. (1996) found that Brock et al. (1992) trading rules had the ability to predict UK returns if sufficiently long series of stock indices were considered. However, no significant gains were found after factoring in trading costs. The results were seen to support the weak form efficiency of UK financial markets.

Ratner & Leal (1999) examined potential profits of ten Variable Length Moving Average (VMA) technical trading rules in ten emerging equity markets of Latin America and Asia. The findings indicated that VMA trading rules did not possess widespread ability to profitably forecast future stock price movements in most of the researched emerging markets, especially after trading costs were considered. 82 cases out of 100 provided a correct indication of market behavior when statistical significance was disregarded. 21 of these included statistical significance even after trading costs. However, these were concentrated in certain markets and finally the authors concluded that only three of the markets may have provided possibilities for profitable technical trading.

Isakov & Hollistein (1999) tested if the use of simple technical trading rules is profitable with Swiss stock prices. They used several *moving average* trading rules and *oscillators*[12] such as *relative strength index*[13] and *stochastic indicator*[14]. These rules were applied to daily returns of Swiss Bank Corporation General Index for the period 1969-1997. They found that the most profitable rule was a moving average with averages computed for one and five days. The results also show that the use of oscillators was not a great help to improve performance. Finally, they concluded that, although average results indicated transaction costs to eliminate technical trading profits in the Swiss

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[12] Oscillators will be discussed in chapter 5.6.
[13] Relative strength index trading rule will be discussed starting from chapter 5.6.
[14] Stochastic indicator trading rule will be discussed in chapter 5.6.

stock market, there are conditions where moving average trading rules may have been profitable. An investor with low transaction costs, not higher than 0.3-0.7% per transaction, could have applied these techniques successfully.

3 MARKET EFFICIENCY

As this study aims at evaluating the capital market efficiency, the following chapters first introduce the concept of market efficiency, often referred as Efficient Market Hypothesis (EMH). However, to be able to describe the assumptions and conditions of efficient markets, the perfect capital markets are first explained. After this the market efficiency is described by starting with the conditions and categories of market efficiency. This is followed by the characteristics of common efficient market models. The main interest lies in the last chapter including more detailed description of the forms of market efficiency and the ways the efficiencies can be empirically evaluated.

3.1 Perfect Capital Markets

When discussing market efficiency the role of perfect capital markets is essential since perfect capital markets are efficient using any concept of market efficiency. According to Copeland & Weston (1988) the following conditions are met in a perfect capital market:

1) Markets are frictionless i.e. there are no transaction costs or taxes, all assets are perfectly divisible and marketable and there are no constraining regulations.
2) There is perfect competition in product and securities markets. In product market this means that all producers supply goods and services at minimum average cost and in securities markets this means that all participants are price takers.
3) Markets are informationally efficient i.e. information is costless, and it is received simultaneously by all individuals.
4) All individuals are rational expected utility maximizers.

Given these conditions both product and securities markets will be also efficient. Below the efficient markets, and especially efficient capital markets, are discussed in more detail.

3.2 Efficient Capital Markets

According to Fama (1970), in order to be efficient, the sufficient conditions for a capital market can be determined as:

1) There are no transaction costs in trading securities.
2) All available information is costlessly available to all market participants.
3) All agree on the implications of current information for the current price and distributions of future prices of each security.

In such a market, the current price of a security obviously "fully reflects" all available information. (Fama 1970) This means that when assets are traded, prices are accurate signals for capital allocation and no unexploited profit opportunities will exist in the market.

Capital market efficiency is much less restrictive than the notion of perfect capital markets. To show the difference between perfect and efficient capital markets some of the perfect market assumptions can be relaxed. For example, there can still be efficient capital markets if markets are not frictionless. Prices will still fully reflect all available information if, e.g., securities traders have to pay brokerage fees or if an individual's human capital (which, after all, is an asset) cannot be divided into a thousand parts and auctioned off. More important, there can be imperfect competition in product markets and there still are efficient capital markets. (Copeland & Weston, 1988)

The market efficiency is divided further into following categories:

1) Information efficiency
2) Allocational efficiency
3) Operational efficiency

Following Fama (1970) security market efficiency is usually defined as *informational efficiency* in the sense that security markets are efficient when prices instantaneously and fully reflect all available information. Informational efficiency implies that there is no information that could be used to obtain a better predictor of the price of a security tomorrow than today's price adjusted for the expected daily return of an asset in the same risk category. (Berglund 1986)

It has been insisted that informational efficiency cannot be achieved in reality. A capital market could be strictly informationally efficient only if information processing required no resources (Berglund 1986).

Also technical analysis relies on this assumption. Although all relevant information would affect the prices, the new information is supposed to be followed by an adjustment period, because relevant information is unequally available and finally the implications of current information of are disagreed.

On the other hand, market efficiency is not as strictly defined as the informational efficiency. The market can be considered as efficient although there was information not reflected in the stock prices. The prerequisite of market efficiency is that there exists no possibility to gain profits exceeding the ones investors may gain on average. The possible new information not included in the stock prices is irrelevant, if the information can't be profitably used. Therefore, the market efficiency can be present also in real life.

A market is said to be *allocationally efficient* when prices are determined in a way that equates the marginal rates of return (adjusted for risk) for all producers and savers. In an allocationally efficient market, scarce savings are optimally allocated to productive investments in a way that benefits everyone. (Copeland & Weston 1988)

Operational efficiency deals with the cost of transferring funds. In the idealized world of perfect capital markets, transaction costs are assumed to be zero; therefore perfect operational efficiency exists. (Copeland & Weston 1988)

3.3 The Efficient Market Models

Market efficiency is also often evaluated by exploring the characteristics of market time series data. This chapter introduces the four most common efficient market models that interpret the behavior and possible correlation of consecutive prices of assets. The models are Fair Game, Random Walk, Submartingale and Martingale. The last three ones are actually special cases of Fair Game model, but still they all play an important role in empirical literature (Fama 1970).

According to Fama (1970) the properties of these expected return models are implications of the assumptions that:

1. The conditions of the market equilibrium can be stated in terms of expected returns.
2. The information is fully utilized by the market in forming equilibrium expected returns and thus current prices.

According to these models, a market can be considered as efficient, when investors can't use the information to gain abnormal profits. Therefore, the assumptions have a major empirical implication – they rule out the possibility of trading systems based only on information at moment t that have expected profits or returns in excess of equilibrium expected profits or returns. (Fama 1970)

The equilibrium expected return on a security is a function of its risk. Different theories would differ primarily in how risk is defined. (Fama 1970) These members of the class of Expected Return Theories are summarized below and described more accurately with equations in the appendix A.

3.3.1 Fair Game

The fair game model is based on the behavior of average returns. A fair game means that, on average, across a large number of samples, the expected return on a security equals its actual return.

More precisely, as can be seen in the appendix A, the information indicated with Φ reflects in share j price $p_{j,t}$. If company prospects could be forecasted without uncertainties, the information Φ_{t+1} would be identical with Φ_t. In this case the share price differences p_t and p_{t+1} would not be consequences of new information flowing in the market. In reality Φ_{t+1} differs from Φ_t i.e. the prospects are not sure. Consequently, p_{t+1} is supposed to include a risk margin that an investor takes when relying on Φ_t. This margin size is directly correlated to information uncertainty.

The trading decisions based on Φ_t can't provide higher expected returns than defined by market equilibrium. The expected price difference between p_{t+1} and p_{t+1} forecasted at moment t with information Φ_t is *zero*. At moment t these price (and return) differences are a "fair game" with respect to information Φ_t.

3.3.2 Random Walk

In the early treatments of the efficient market model, the statement that the current price "fully reflects" available information, was assumed to imply that (Fama 1970):

1. The successive price changes (or more usually, successive one-period returns) are independent.
2. Successive changes (or returns) are identically distributed.

Together the two hypotheses constitute the random walk model, which is a special case of the fair game model. In general, the basic assumption behind the model is that market prices are based on a random process. According to the first assumption, information arrives to the market randomly and the effects on prices are random. The share prices are, consequently, random and the historical price information has no value. The latest price includes all the information included in the previous prices. According to the second assumption the price increases and decreases are equally probable. The model can be expressed with an equation shown in the appendix A.

In the simplest random walk process, each successive change in y_t is drawn independently from a probability distribution with 0 mean. Thus, y_t is determined by

$$y_t = y_{t-1} + \varepsilon_t, \tag{1}$$

where y_t = the value at time t, y_{t-1} = the value at time t-1 and ε_t = a random value around the average at time t. Such a process has expected value $E(\varepsilon_t) = 0$ and could be generated by successive flips of a coin, where a head receives a value of +1 and a tail receives a value of –1 (Pindyck & Rubinfeld 1982).

The term random has some unfortunate connotations. Random events are often believed to be in some sense “uncaused”. But there is nothing mystical or unnatural about the process that generates stock price changes. The random movement of stock prices simply results from competition between a large number of skilled and acquisitive investors (Brealey 1987).

There exist special cases of random walk. For example, a time series could be a random walk around a deterministic trend i.e. the time series could be the sum of a deterministic trend and a random walk. This gives one special case of random walk, random walk plus drift model.

Both pure random walk and random walk with drift are non-stationary stochastic processes with variances that increase indefinitely. In the case of the pure random walk, the unconditional mean (the expected or long run value) is its initial value, whereas for a random walk with drift the mean is not constant. The inclusion of the drift term models a tendency for a series to increase or decrease on average.

Random walk hypothesis can be tested by surveying the abovementioned assumptions related to correlations and distributions. As random walk is not valid if the subsequent prices are correlated, in this study the autocorrelation tests are used to evaluate the random walk on selected markets. The final purpose is to reveal the possibilities of technical analysis and market inefficiencies.

3.3.3 Submartingale and Martingale

Two other special cases of Fair Game model are submartingale and martingale. The submartingale model is a fair game with non-negative returns. Submartingale includes a statement that the price sequence p_{jt} for security j follows a submartingale with respect to the information sequence Φ_t, which is to say nothing more than that the expected value of next period's price, as projected on the basis of the information Φ_t, is *equal* to or *greater* than the current price (Fama 1970).

The martingale model is a fair game, where tomorrow's price is expected to be the same as today. In other words, it assumes that the expected profit and price change are zero. Equations for both submartingale and martingale are again shown in the appendix A.

On an efficient market the prices do not have to follow a submartingale, nor do accumulated excess returns have to follow a martingale, which is the case on an informationally efficient market. However, on an efficient market trading in securities should still be a fair game in the sense that excess returns cannot be obtained by trading on information not used by the market. In other words, systematic patterns in prices and delayed price reactions on new information may exist as long as no one can use this information to achieve excess returns. (Berglund 1986)

3.4 Forms of Market Efficiency

As already mentioned, market efficiency can be divided further to different forms of market efficiency. Fama (1970) defines three types of efficiency, each of which is based on a different notion of exactly what type of information is understood to be relevant in the phrase "all prices fully reflect all *relevant* information" (Copeland & Weston 1988). These are:

1. Weak form market efficiency
2. Semi-strong form market efficiency
3. Strong form market efficiency

According to French (1989) the forms of market efficiency can be binded with each other. If a market is considered to be strong form efficient, it also has to be semi-strong and weak form efficient. Accordingly, a semi-strong form efficient market also has to be weak form efficient.

Below the forms of market efficiency are presented in more detail. The main interest lies in the ways these different forms can be tested.

3.4.1 Weak Form Market Efficiency

According to the weak form of the efficient market hypothesis, the information contained in the historical sequence of prices is fully reflected in current market data. Thus, e.g. analysis of past price and volume patterns to predict the future will be useless. Tomorrow's price change will reflect only tomorrow's news and will be independent of the price change today. Since news is unpredictable, the resulting price changes must also be unpredictable and random. Thus, one of the characteristics of the price series is that all subsequent price changes are random departures from previous prices i.e. follow random walk.

The weak form efficiency has been explored with different statistical methods that can reveal the correlation between subsequent price movements. These methods include autocorrelation and runs tests etc. However, the lack of randomness is not enough. Although the price movements were not random, an investor using historical data appropriately for trading decisions must be able to gain abnormal profits when compared to the average investors. This can be tested by simulating active trading in researched markets.

Like mentioned in the chapter 2 summarizing previous researches, to estimate the weak form market efficiency, also seasonalities have been frequently researched. However, according to Berglund (1986), seasonality is considered as a subject only closely related to weak form efficiency and therefore closer description is excluded in this study.

3.4.2 Semi-Strong Form Market Efficiency

When tests seemed to support the weak form efficiency, attention was turned to semi-strong form of EMH. Now, not only historical information, but all publicly available relevant information is assumed to be fully reflected to current market prices. If markets are efficient in this sense, also the technique of fundamental analysis i.e. analysis of any information concerning a company and general economy, will not yield abnormal profits. In other words, in semi-strong form tests the concern is the speed of price adjustment to other obviously publicly available information (Fama 1970).

Thus, semi-strong form efficient markets are considered to provide a reliable source of information also for the investors without insider information or specific information processing capabilities.

Like in the case of weak form efficiency, the conditions of semi-strong form efficiency can be fulfilled even if statistical methods would reveal the market not to follow random walk and therefore appear as inefficient. However, the efficiency requires again that new information cannot be profited economically e.g. due to transaction costs and costly information.

Early tests of the semi-strong form of market efficiency were conducted by studying the announcements of stock splits and dividends. To a certain extent these actions are considered to be reasonably easy to predict, even before an official announcement is made. Similar reflections of market efficiency are market reactions on events such as public announcements of new offers, financial statements, changes in accounting or reporting methods, large block transactions, repurchase tender offers etc.

The second forum for testing the semi-strong form was to look at the recommendations of brokerage houses and the performance of mutual funds. The professional analysts are presumed to have all the available information in the market.

There are also other ways stated to be suitable for evaluating semi-strong form market efficiency. For example, efficiency has been estimated by exploring the accounting magic i.e. the principles behind financial statement creation. However, so far the different areas of interests in different researches have been based on slightly different researcher assumptions. As the research results may vary, now the question is, may a market be efficient regarding certain published market information, while it is inefficient related to another kind of information (Malkamäki & Yli-Olli 1988).

3.4.3 Strong Form Market Efficiency

According to the strong form of EMH, market prices fully reflect all information that is known to any market participant. The market prices again indicate the correct price level and the information processing does not profit anyone.

Since studies indicate that stock splits, dividend increases and mergers announcements can affect share prices, it could be expected that illegal insider trading with such information could profit before the announcement. Thus, if investors with privileged information can make abnormal profits, strong-form market efficiency is not met.

The strong form market efficiency can be basically estimated in two different ways. First category includes tests aiming to reveal whether abnormal profits are caused by insider information. As the actual use of insider information has been difficult to identify, the researches have concentrated on evaluating if abnormal profits have been gained by parties with an access to insider information. (Malkamäki & Yli-Olli 1988) In other words, the concern is whether any investors or groups that have monopolistic access to any information relevant for the formation of prices have recently appeared (Fama 1970).

The second category includes the researches trying to reveal if professionally managed funds have been able to gain abnormal profits. Again, the purpose is to reflect skillful use of published information or the use of insider information. (Malkamäki & Yli-Olli 1988)

3.4.4 The More Recent Categorization

Market efficiency has been researched frequently after the classification presented by Fama (1970). More recent researches have revealed new information and consequently Fama (1991) revised the categorization. Instead of weak form, semi-strong form and strong form tests the new categories were now

1. *Tests for return predictability*, which also includes the burgeoning work on forecasting returns with variables like dividend yields and interest rates. Since market efficiency and equilibrium-pricing issues are inseparable, the discussion of predictability also considers the cross-sectional predictability of returns, that is, tests of asset-pricing models and the anomalies (like the size effect) discovered in the tests. Finally, the evidence that there are seasonalities in returns (like January effect), and the claim that the security prices are too volatile is also considered under the rubric of return predictability.
2. *Event studies*, which includes the old semi-strong form tests i.e. evaluation how the prices adjust to public announcements.
3. *Tests for private information*, which includes the old strong form tests i.e. whether specific investors have information not in market prices. (Fama 1991)

It can be noted that the actual change has been made to the first category. For the second and third categories the changes have been made in title, not in coverage.

4 TECHNICAL ANALYSIS

Like mentioned above, technical analysis is often used for evaluating market efficiency. This chapter takes a closer look at the principles behind technical analysis. First the basic assumptions of technical analysis are introduced. As technical analysis is claimed to originate from Dow Theory, this is described also in its own chapter. After this the actual use and common interpretations of technical analysis are described. As the opinions on technical analysis differ considerably, the final chapters list the insisted pros and cons of technical analysis including the suggestions concerning its suitability for investing and market efficiency evaluation purposes.

4.1 Basic Assumptions

The philosophy of technical analysis is based on three assumptions:

1. Market action discounts everything
2. Prices move in trends
3. History repeats itself

1. Market action discounts everything - all the fundamental, political, psychological etc. information is reflected to a daily price. The price finally determines the balance between demand and supply. If the demand exceeds the supply, the price will rise and vice versa. Consequently, the price movements form the basis for the analysis.

Still timing differs the assumption from the theory of efficient market. Technical analysts assume the market prices to reflect the relevant information only gradually as the market participants realize the effects of the information. (Nordin et al. 1989) This adaptation of different participants is related to their skills and knowledge and consequently the price changes of securities and indices are insisted not to be random. Due to differences of market participants, e.g. due to different psychological factors and data processing capabilities, efficient market would possibly require allowance similar to horse races. When this is compared to the assumptions of the efficient market, the delay directly indicates that technical analysis theory assumes the markets to be inefficient.

2. *Prices move in trends* - the main target of technical analysis is to detect the trends as early as possible. If the trend is rising, the shares should be bought and held until there appear signs of a decreasing trend.

Further, once a trend is initiated, it is assumed to continue the same direction more likely than to change the direction. On a positive season, e.g. market boom, the trend can be assumed to be increasing for months, even for years. (Nordin et al. 1989)

3. *History repeats itself* - technical analysis assumes that varying market circumstances sustain similar psychological reactions in the public. In other words, the technical approach is based on the theory that people behave in the same way in similar situations and stock markets reflect this mass psychology. According to this approach, analysis basically attempts to forecast future price movements based on the assumption that crowd psychology moves between panic, fear and pessimism on one hand and confidence, excessive optimism and greed on the other (Pring 1991). For example, people sell shares, when the prices collapse. Accordingly, when the prices are high people still want to buy (Nordin et al. 1989). This behavior is maintained by the news announced by media.

As price changes are usually considered as sums of different estimations of market participants analyzing the information according to their capabilities, similar average reactions and information processing skills have been stated to remain in the market. Now a technical analyst should be able to analyze the market e.g. by exploring repeated market and trend patterns, but also correlations between the price changes and/or between price changes and changes in other data like volume.

4.2 Dow Theory

The basic assumptions presented above and the whole technical analysis is considered to be based on Dow Theory. This was named after its creator, *The Wall Street Journal* establisher Charles Dow, who is considered to be the grandfather of most technical analysis (Bodie et al. 1999). Dow originally did not target on predicting market development, but used the theory for evaluating the general economical situation, mainly in US. However, the theory was stated to be especially useful for identifying long-term trends in stock market prices.

The Dow Theory is based on the following six basic tenets:

1. Averages discount everything
2. A market has three trends
3. Major trends have three phases
4. The two averages must confirm
5. Volume must confirm the trend
6. A trend is assumed to be in effect until it gives definite signals that it has reversed

1. Averages Discount Everything - because averages reflect the combined market activities of thousands of investors, including those with the best information and foresight on trends and events, the averages in their day-to-day fluctuations discount everything known, everything foreseeable, and every condition which can affect the supply or demand for securities. Even unpredictable natural calamities are quickly appraised and their possible effects discounted. (Edwards 1992) The discounted information can originate e.g. from fundamental analysis, politics or psychology. The tenet is the same as the first assumption of technical analysis mentioned above.

2. A Market Has Three Trends - a market swings in trends, of which the most important are its *major* or *primary* trends. These usually last at least for a year, but they may run even for several years (Edwards 1992). When the primary trend is up (*bull market*), the next top and bottom prices are above the previous ones. Conversely, when each intermediate decline carries prices to successively lower levels and each interventing rally fails to bring them back up to the top level of the preceding rally, the primary trend is down (*bear market*) (Edwards 1992). The primary is the only trend with which a longer-term investor is concerned. His aim is to buy stocks as early as possible in a bull market –as soon as he can be sure that one has started – and then hold them until it becomes evident that the bull has ended and the bear market has started (Edwards 1992).

The *secondary* trends are reactions that interrupt the progress of prices in the primary direction. They are the intermediate declines or *corrections,* which occur during bull markets, or alternatively the intermediate rallies or *recoveries,* which occur in bear markets. (Edwards 1992) The duration of a secondary trend is estimated to vary between three weeks and three months.

The *minor* trends are brief fluctuations that are – so far as the theory is concerned – meaningless in themselves. Therefore, interferences drawn from these day-to-day fluctuations are quite apt to be misleading. The minor trend is also the only trend that can be manipulated. (Edwards 1992)

3. *Major Trends Have Three Phases* - both up and down trends have three phases. The first phase of the primary uptrend is *accumulation* during which farsighted investors, sensing that business is due to turn up, buy the shares offered by discouraged and distressed sellers, and raise their bids gradually as such selling diminishes in volume. (Edwards 1992)

The second phase is one of fairly steady advance and increasing activity as the improved tone of business and a rising trend in corporate earnings begin to attract attention. (Edwards 1992)

Finally comes the third phase when the market boils with activity as also the public starts the investment activity. The market is now reaching the stage where it might be more appropriate to start selling. In final of this phase, with wild speculation, volume continues to rise, but "air pockets" appear with increasing frequency (Edwards 1992).

Primary downtrends are also usually characterized by three phases. The first is the *distribution* period, which actually starts in the later stages of the preceding bull market. Trading volume and prices are still high. The careful investors start selling before the second phase, which is called the *panic* phase. The downward trend of prices suddenly accelerates into an almost vertical drop. After the panic phase, there may be a fairly long secondary recovery or a sidewise movement, and the third phase (without specific name) begins. The business news now begin to deteriorate. (Edwards 1992). The bear market ends when everything in the way of possible bad news has been discounted.

4. The Two Averages Must Confirm - Dow Theory looks only at the movements of the Dow Jones Transportation (DJTA) and Industrial Averages (DJIA). The movements of both averages should be evaluated together. The DJIA is considered as the key indicator of underlying trends, while the DJTA usually serves as a check to confirm or reject the DJIA signals. Conclusions based on the movement of one average, unconfirmed by the movement of the other, are supposed to be erroneous. The signals do not have to occur simultaneously, but the closer together the better (Murphy 1986). Consequently, when the two averages diverge from each other, the prior trend is assumed to be still in effect. From all Dow principles this is the most often questioned one and the one most difficult to rationalize.

5. Volume Must Confirm the Trend - trading activity tends to expand as prices move in the direction of the prevailing primary trend. Thus, in a bull market, volume increases when prices rise and dwindles as prices decline. (Edwards 1992) Decreasing volumes during a bull market are supposed to give a sign of correction (Nordin et al. 1989). Respectively, during a bear market, volume should be higher during the downward sloping trend and decrease during the corrections against the trend.

According to Dow Theory, the volume is just a secondary tool for confirmimg the price data development (Nordin et al. 1989). Further, there are exceptions, but useful conclusions can seldom be drawn from the volume behavior of just a few days. It is only the overall and relative volume trend over a period of time that may produce helpful indications (Edwards 1992).

6. A Trend Is Assumed to Be in Effect Until It Gives Definite Signals That It Has Reversed - what the tenet states is really a *probability*. It is a warning against changing one's market position too soon. (Edwards 1992) It has been declared that, after the first signals indicating the trend to change, the investor should wait for confirmation. However, the longer the trend is trusted, the more sensitively the signals should be interpreted.

4.3 Use and Interpretation

According to Pring (1991) the technical analysis can be used for two purposes. The preferred use is to incorporate a well-thought-out mechanical trading system to alert the investor that a trend reversal i.e. trend turn has probably taken place. In this use a mechanical trading system is an important filter, but represents just one more indicator in the decision-making process.

The other way to use a mechanical trading system is to react on *every* signal. If the system is optimized correctly, on the long run it should mechanically generate profits and simultaneously provide an evaluation of the overall market development.

This study sees technical analysis as a mechanical trading tool. For investors it is supposed to provide the tools for successful trading activity by giving trading signals based on certain rules.

The analysis methods is divided in two main categories i.e. indicator and graphical analysis. In indicator analysis, the investors research the data by calculating indicators. Once the indicator and appropriate parameters are chosen, the results do not necessarily require any interpretation. In graphical analysis investors evaluate the historical graph and based on the graph shape forecast the future movements. The presentation, however, has to be now also interpreted according to considerably subjective criteria. Different methods are described in more detail in chapter 5.

As different indicators may give completely different estimations and signals for the investor, the trading systems should be optimized case by case, according to the shares and markets. After the method selection, the mechanical approach includes new challenges as the numerous trading rule parameters have to be decided. According to Bookstaber (1985), the difficulty in arriving at the correct parameter values is of more importance than the selection of the system itself. The optimal parameter selection still does not provide profits after every transaction, which makes the optimizing even more difficult.

The differences between different indicators can also be utilized. To avoid false interpretations, the observations and signals can be double-checked with simultaneous use of several indicators.

The data employed in the analysis is usually price data including open, high, low and/or close prices. However, market estimations can be drawn with other data series such as trading volumes or already modified information like averages etc.

4.4 Aspects Supporting Technical Analysis

The doubts on market inefficiencies support the use of technical analysis. Like mentioned earlier, on an inefficient market the information is not always considered to be adapted immediately and correctly on the market. Also Pring (1991) refers to different psychological factors questioning the importance of information availability and processing. He mentions that one of the great difficulties of putting theory into practice is that a new factor – emotion – enters the scene as soon as money is committed to the market. Therefore the history should be studied as the market may react again in similar manner.

While emotion and psychological factors annul the market efficiency, technical analysis is considered as a tool for exploiting this irrational behavior. The following advantages, summarized by Pring (1991), are based on this positive characteristic of mechanical trading and assume that an investor will follow the buy and sell signals consistently:

1. The major advantage of a mechanical trading system is that it automatically decides when to take action; this has the effect of removing emotion and prejudice.
2. Most traders and investors lose in the marketplace because they lack discipline. Mechanical trading requires only one aspect of discipline, the commitment to follow the system.
3. A well-defined mechanical system will give greater consistency of profits than will a system in which buying and selling decisions are left to the individual.

4. A mechanical system will let profits run in the event that there is a strong uptrend but automatically limit losses if a whipsaw signal occurs.
5. A well-designed model will allow the trader or investor to participate in the direction of every important trend.

Naturally some of the statements seem overoptimistic. A well-defined system is, however, a rare case of technical analysis. The structuring of such a system has to be based on several subjective criteria and requires the market to maintain similar characteristics over time.

On the other hand, as mentioned in the chapter 2, also the previous study results have been often argued and the studies have been repeated. Usually too positive results have been replaced with new figures where e.g. transaction costs or participation of risk level has changed the superiority of trading rules. Still these more recent surveys have admitted that certain rules may have generated abnormal profits earlier and that the decrease of profit level may be caused by recently increased market efficiency.

If the EMH is ignored, the pros of technical analysis have been considered to be related to the speed and easiness of the methods. The year, month, week, day, hour or even minute-level forecasts can be implemented with data that is easily available. Also the theories and methods are simple and publicly available while the practical work can be easily implemented with computers. It is also easy to follow different markets simultaneously, which enables the investor to select tempting markets, to estimate intermarket correlations etc.

While mechanical trading rules give clear trading signals it has been claimed that also the trading signals may provide other unique information. Because the financial market is correlated with the overall economy, technical analysis can be used to forecast the financial market but also to forecast the development of the economy. For example, while the general economy indicators estimate the uptrend to continue, the trading signals may indicate opposite.

4.5 Aspects Criticizing Technical Analysis and Previous Studies

Like mentioned above, the previous researches surveying weak form market efficiency and technical analysis profitability have sometimes been criticized. For example, although the previous researches provide evidence that technical trading rules may be capable of producing superior performance, this evidence is considered to be affected by the widely recognized data-snooping biases. For example, Malkamäki & Yli-Olli (1988) stress that surveying weak form efficiency is problematic. In principle there exists an indefinite number of combinations of past and future data used to measure the correlation. Thus, they conclude that it is impossible to prove whether past data could or could not be used to forecast future.

On the other hand, the possibility to generalize the research results and, hence, the size of information set used in efficiency evaluation has been discussed. It is apparently easier to test efficiency with respect to information contained in a limited set of information than to test for efficiency with respect to the whole universe of information. According to Berglund (1986), it is practically impossible to prove or verify that a market has been efficient with respect to a larger information set. This is also concluded e.g. by Bessembinder & Chan (1998) who finally insist that there is little reason to view the test results as indicative of market inefficiencies. Still, they view the evidence, that the simple technical rules do contain forecast power, to be still fascinating.

Further, Sullivan et al. (1999) state that there are reasons to believe that a strategy, a research has proven to be profitable, may not work in practice. Even if the actual trading costs would not be higher and the time it takes to make the actual trades would not be longer, technical trading rules that historically have been successful are also the ones most likely to catch the attention of researchers because they are the ones promoted by textbooks and the financial press. Hence, even though individual researchers may act prudently and do not experiment extensively across trading rules, the financial community may effectively have acted as such a filter. For example, Ready (1997) showed that the repetition of Brock et al. (1992) methodology couldn't be used profitably with more recent data.

Also Brealey & Myers (2000) state that the reported method profitability will be filtered out making the market finally follow EMH. If past price changes could be used to predict future price changes, investors could make easy profits. But in competitive markets profits don't last. As investors try to take advantage of the information in past prices, prices adjust immediately until the superior profits from studying past price movements disappear. As a result, all the information in past prices will be reflected in today's stock price, not tomorrow's. Patterns will no longer exist and price changes in one period will be independent of the changes in the next (Brealey & Myers 2000).

Price adjustment is assisted by the improved automated data processing capabilities providing the equal information for different investors. It has been insisted that also several commercial portfolio management applications utilize technical analysis, which finally affects the price levels appropriately and the analysis becomes useless.

However, hesitating is assumed to affect the possible filtering. Although several technical analysts would agree on the market direction, everybody doesn't act simultaneously in the same way. Others try to predict the change while others are still waiting for confirmation. Thus, technical analysis cannot necessarily change the supply-demand ratio in the level that would affect the trends.

Also the usability of technical analysis and especially the need for subjective interpretation has caused discussion. Especially, when several methods are used simultaneously, technical analysis is not always that precise and straightforward tool. If an investor picks and chooses which signal to follow without other independently based technical criteria, the risk of making emotional decisions is realized, losing the principle benefit of the mechanical approach (Pring 1991).

In addition to the different methods and analysis results, also the theory itself has been stated to require interpretation. Edwards (1992) concludes that the whole utilization of Dow Theory is a matter of interpretation. Even the most experienced and careful Dow analysts find it necessary occasionally to change their interpretations.

The disadvantages summarized by Pring (1991) translate the abovementioned characteristics to more practical level investment advice. The main points are listed below:

1. No system will work all the time, and there may be long periods when it will fail to work.
2. Using past data to predict the future isn't necessarily a valid approach because the character of the market often changes.
3. "Back-testing" won't necessarily simulate what actually would have happened. It is always not possible to get an execution at the price indicated by the system, because of illiquidity, failure of your broker to execute orders on time, and so forth.

Naturally, also the Dow Theory tenets are considered to include some downsides. The main points, described by Edwards (1992), have been listed below:

1. The theory is too late. The buy and sell signals are considered to come too late.
2. The theory does not help an intermediate trend investor. The theory gives little or no warning about the changes in an intermediate trend.
3. A man cannot buy or sell the averages. Although most stocks tend to go with the trend, the Dow Theory does not and cannot tell you what stocks to buy (Edwards 1992).

5 METHODS USED IN TECHNICAL ANALYSIS

This chapter provides an overview for more practical technical analysis in the form of common analysis tools. A brief introduction to the wide variety of graphical analysis tools is followed by a summary of most common simple trading rules. To be able to describe the wide variety of different trading rules even in very general level, they are categorized based on classes presented in previous academic studies and technical analysis literature.

The main interest lies in the use and usefulness of different methods and the aim of the comparison is to provide a basis for trading rule selection used in this study. The selected trading rules will be described in more detail only in the next chapter 6.

5.1 Graphical Analysis

In addition to the mechanical trading methods, technical analysis tools include also the graphical instruments that can be used to illustrate the time series development. Although trading with graphical analysis is usually based on subjective chart interpretation, to support the trading rule summary starting from chapter 5.2, the first chapters here illustrate how different chart types are used in technical trading.

Some of the most common chart types are described below. These are line, bar, candlestick and point & figure charts.

5.1.1 Line Charts

The line chart is one of the simplest charts. In practice, over time a plot forms a line presenting data history, which can be used for a visual illustration, but also with particular methods to provide trading signals. Exemplary ways to employ line charts in technical analysis can be found in chapter 5.3.

Although most of the methods interpreting the graphs can be applied to various chart types, line charts are popular. Since lines are thin compared to bars, the data displayed in the front does not block out the data behind. It is also typical to complement line charts with other chart types.

5.1.2 Bar Charts

The bar chart is perhaps the most popular charting method. A bar chart includes a group of bars in chronological order. The high, low and close are required to form the plot for each period of a chart. The high and low are represented by the top and bottom of the vertical bar while the close is indicated with a horizontal line crossing the vertical bar. It is also common to show the closing price on the right side of the bar and the opening price on the left side of the bar. Below is an example of a bar chart.

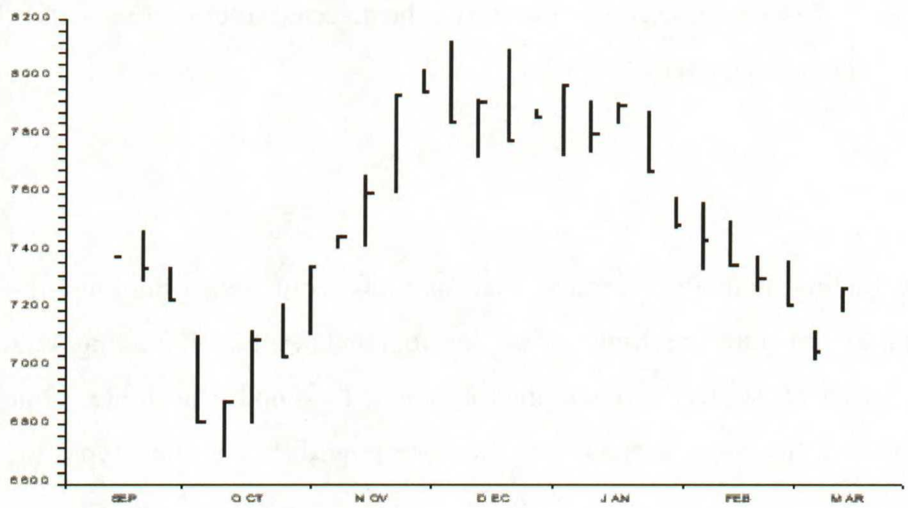

Figure 2 Weekly bar chart of BUX index of Budapest Stock Exchange
The chart includes data from the last half year of the research period.

Bar charts are an ideal tool for analyzing the close or open relative to the high and low. The chart needs interpretation and is therefore often completed with other analysis methods to provide forecasts and trading signals. To illustrate the possibilities for speculations, some interpretations used with bar charts are listed here:

- The first step in interpreting a bar chart is to identify the trend. An uptrend includes a series of bars where highs and lows are higher when compared to the values of previous bars. Respectively, a downtrend is a series of bars with lower highs and lower lows.
- The eagerness of buyers and sellers is indicated by the position of the closing price when related to the close on the preceding bar. The larger the distance, the greater the eagerness.
- Range is the distance between the high and the low on a bar. Expanding ranges in an uptrend signal increasing eagerness from buyers and increasing eagerness from sellers in a downtrend. Contracting ranges indicate decreasing eagerness.

5.1.3 Candlestick

Similar to bar charts, candlestick charts also display the open, close, high and low. The difference is the use of shapes and color to show if the stock was up or down over the day. A candlestick has two parts, the *body* and the *tails*. If the body is filled in (blue), the stock price has gone down during that time period, while the top of body is the open price and the bottom of the body is the close. If the body is not filled in (white), the stock price has gone up during that time period, while the bottom of the body is the open and the top of the body is the close. If the stock price did not change, a horizontal line will represent the body. The tails, or vertical lines, extending from the body show the high and low prices during that period. Below is an example of a candlestick chart.

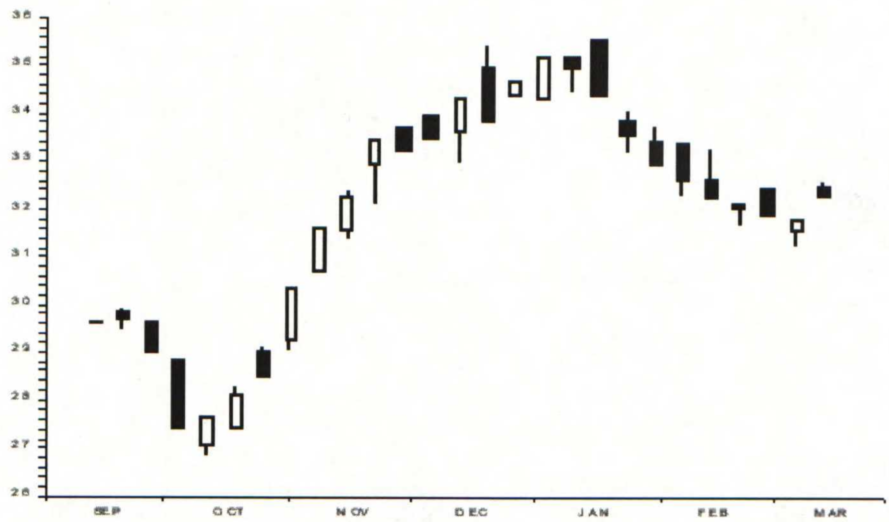

Figure 3 Weekly candlestick chart of BUX index of Budapest Stock Exchange
The candlestick chart includes data from the last half year of the research period.

The advantage of candlesticks is the ability to highlight trend weakness and reversal i.e. trend turn signals that may not be apparent on a normal bar chart. There are several patterns the investors focus on when using candlestick charts. Basically these patterns can be applied also in bar charts and vice versa. For example, bullish and bearish patterns are claimed to have the following features: In a bullish pattern, the stock opened near its low and closed near its high. In an opposite bearish pattern, the stock opened near its high and dropped substantially to close near its low. Other popular patterns are called hammer[15], star[16] and doji[17].

[15] A hammer is identified by a small body along with a large range. This is a bullish pattern only if it occurs after the stock price has dropped for several days. The point is that this pattern might indicate a reversal in the downtrend.
[16] A star appears when a small body candlestick gaps above the previous body. This means that a tiny body candlestick opens and closes the following day outside the original body. Mostly, stars typically indicate reversal or indecision.
[17] Doji is a form where security's open and close are virtually equal. Alone, doji is a neutral pattern.

5.1.4 Point & Figure

The second charting method similar to the bar chart is Point & Figure (P&F) where only the significant price movements are described with letters X and O. The idea is that P&F charts help the investor to filter out less-significant price movements and enable focusing on the most important trends. Little or no price movement is deemed irrelevant and therefore not duplicated on the chart.

In practice, price movements are combined into either a rising column of X's or a falling column of O's. By convention, the first X in a column is plotted one box above the last O in the previous column and the first O in a column is plotted one box below the highest X. The logic can be best described with an exemplary point and figure chart below.

Figure 4 Point & figure chart of BUX index of Budapest Stock Exchange
The chart includes data from the last half year of the research period. The applied parameters in this exemplary chart are box size of 2 and reversal amount of 1.

Box size and *reversal amount* are the two attributes that define the appearance of a P&F chart. Each X or O occupies what is called a *box* on the chart. The sensitivity of the chart can be varied by altering the *box size*. The box size is the minimum price movement recorded and serves to eliminate minor fluctuations. Larger box sizes are used for charting longer periods. The *reversal amount* defines how much a stock needs to move in the opposite direction before a *reversal* occurs. Whenever this reversal threshold is crossed, a new column is started right next to the previous one, only moving in the opposite direction.

P&F charts differ from traditional price charts so that they completely disregard the passage of time and only price changes are displayed. Rather than having price on the y-axis and time on the x-axis, P&F charts display price changes on both axes. Therefore, a column of X's or O's may take one day or several weeks to complete. Although Point and Figure charts do not take time into account, they are basically used and interpreted in similar way as the other previously described charts.

5.2 Different Classifications

Now the rest of the chapter 5 concentrates on representing the various methods used when conducting the technical analysis either together with abovementioned graphical tools or just with time series data. To give better overall picture on the universe of various trading rules, the rules are first categorized in classes including methods with similar characteristics. As there exist various technical trading rules, there is also a wide variety of different classifications. First, according to Pring (1991), technical analysis indicators can be divided in three major groups:

1. Sentiment Indicators
2. Flow-of-Funds Indicators
3. Market Structure Indicators

Sentiment indicators monitor the actions and motions of different market participants (Pring 1991). These are also called as expectational indicators as they focus on investor expectations - often before those are discernible in prices. The logic behind the use of such indicators is that different groups of investors are consistent in their actions at major market turning points. This is referred also in the third abovementioned technical analysis basic assumption "history repeats itself".

For an individual security, the price is often the only measure of investor sentiment available. However, for a large market such as the New York Stock Exchange (NYSE), many more sentiment indicators are available. These include the number of odd lot sales i.e. what are the smallest investors doing, the put/call ratio, the premium on stock index futures, the ratio of bullish versus bearish investment advisors, etc.

It has been insisted that sentiment indicator values have been distorted over the past several years. This is due to the widespread use of options and futures of both individual securities and indices.

Flow-of-funds indicators analyze the financial position of various investor groups with an attempt to measure their potential capacity for buying or selling stocks. The price at which each stock transaction takes place must be the same for the buyer and the seller, so naturally the amount of money flowing out of the market must equal what is being put in.

The short interest ratio is perhaps the most widely used indicator of this type. In NYSE this is calculated by taking the monthly NYSE short interest position and dividing it by the average daily volume for the month in question. (Pring 1985)

Flow-of-funds analysis is also concerned with trends in mutual fund and other major institution cash positions. These institutions are normally a source of cash on the buy side. The supply side consists of new equity offerings, secondary offerings, and margin debt (Pring 1991). On the other hand, some technicians believe that looking at liquidity in the banking system is a superior approach as this measures pressure in the banking system and the entire economy.

This money flow analysis also suffers from disadvantages. Firstly, the data is lagged. Secondly, while the data indicates the money available for the stock market, they give no indication of the inclination of these market participants to use this money for the purchase of stocks, nor the elasticity or willingness to sell at a given price on the sell side (Pring 1991).

Market structure indicators form the third area of technical analysis, in which the earlier similar studies and also this study are focusing. Historical price, time, volume and breadth etc. data are inputs for these indicators. Price reflects the level of change in investors' attitudes while time measures the cycle or period of change. Simultaneously, volume measures the intensity of the change in investors' attitudes. Breadth measures how many different securities in the same market are moving in the same direction. The more significant a trend is, the greater the number of securities will be involved in the movement.

Most of the other publications discuss only market structure indicators under heading technical indicators. For example second classification, presented by Bookstaber (1985), discusses only market structure indicators and classifies these further into following three types:

1. The first, and by far the most popular, type includes the trend-following rules. These are designed to pick the turning point of the market, and the development of major price directional shifts in price movements. They obviously will do best in periods of wide market movement, and will be unsuccessful in flat markets. Due to the trend-following nature of the rules, they are also called as lagging indicators. The best known trend-following system is the moving average.

2. The second type of trading rules includes antitrend rules, which are also known as trading-range rules. These generate buy and sell signals from sideways vibrations of flat markets. Trading-range market moves right through the middle of the price fluctuations and therefore an antitrend rule will do best in a market devoid of any sizable price movements, where trend-following systems almost always result in unprofitable signals (Pring 1991). Due to the forecasting nature of the rules, they are also called as leading indicators. For example, oscillators come into their own on a trading-range market (Pring 1991).
3. The third type of trading rule is designed to determine whether a market is in trending or antitrending mode. For example, the trend movement index system is designed to do this. This system can also be adjusted for use as an antitrend system.

Some classifications of market structure indicators include only previous first two categories reflecting different market conditions. For example Pring (1991) classifies first different market conditions to trending and trading-range ones and consequently the rules also just to trend-following and trading-range systems.

Isakov & Hollistein (1999) provide an alternative categorization to lagging and leading methods. This is based on the methods' ability to either indicate the trend existence and confirm the trend continuation or forecast trend reversal. The first class includes indicators that look for patterns in past data usually with graphical analysis. The second class contains rules deriving trading decisions with filters applied in past data.

Together with the majority of previous similar studies, this study concentrates on the market structure indicators divided in trend-following and trading-range ones. As the variety of different trend-following and trading-range rules is wide, to give a better overall picture, these are still divided further. For example, in their research, Sullivan et al. (1999) have divided indicators to five more specific categories. These classes of so-called simple trading rules are Filter Rules, Moving Averages, Support and Resistance, Channel Breakouts and On-balance Volume Averages.

However, to cover better the whole universe of simple different rules, this study represents the common analysis methods below under 4 different headings. These are Trend Analysis, Filter Rules, Moving Averages and Oscillator Analysis. Like mentioned in chapter 2, to maintain the focus of the study, the volume analysis is not discussed here although it would definitely form the fifth equally significant category.

5.3 Trend Analysis

The methods in trend analysis category analyze historical charts. Although also other methods follow trends, as a characteristic, this category indicators utilize the graphical tools for trend recognition. The most common analysis methods are presented below.

5.3.1 Trendlines

In technical analysis literature trendline is considered as an important tool for both trend identification and confirmation. The lines are drawn according to price points that can be tops, bottoms etc. The trendline can then be used e.g. to demonstrate whether the current price is higher or lower than it should be, which can now be interpreted as a possible buy or sell signal. Another popular use of lines connecting several tops or bottoms aims to point out the support and resistance levels described in the next chapter 5.3.2. An exemplary trendline can be seen in the figure 6.

The basic prerequisite for drawing a trend is to be convinced about the trend existence. The significance of a trendline can be estimated e.g. with its duration and, in the case of support and resistance lines, with the number of top or bottom values touching the trendline. The longer the trend is or the more often the prices touch the trendline, the more significant the line is. (Nordin et al. 1989)

The same principles of chart interpretation apply also to other charts than line charts. For example, down trendlines can be constructed on point and figure charts by joining a series of declining peaks. Up trendlines can be drawn by connecting a series of rising lows, and horizontal trendlines can be created by joining identical support or resistance levels. (Pring 1991)

5.3.2 Support and Resistance

In addition to trendlines, the support and resistance (S&R) lines are common tools having also the origin in the abovementioned trendline of Dow Theory. This method has also been referred with different names. For example, the notion of support and resistance has been presented in Brock et al. (1992) study under the title Trading Range Break.

A *support line* is drawn by connecting the bottom values in an uptrend. A support level is a price level at which sufficient demand for a stock appears to hold a downtrend temporarily at least, and possibly reverse it, i.e. start prices moving up again. As long as prices remain above the line, the uptrend is considered solid and intact. A break below the line indicates that net demand[18] has weakened and a change in trend could be imminent.

A *resistance line* is respectively drawn by connecting significant top values in a downtrend. As long as prices remain below the line, the downtrend is again considered solid and intact. A break above the line indicates that net supply is decreasing and a change of trend could be coming up.

Also *trend channels* are based on support and resistance lines. However, a trend channel consists of two *parallel* lines that trace against the trendline. For example, if connecting the price bottoms of a particular stock or index compose an upward sloping line parallel to a line connecting the tops of that stock or index, the ascending trend channel is the area between the two lines. Descending and horizontal trend channels are formed respectively. Figure 5 below illustrates exemplary support and resistance lines forming a horizontal trend channel.

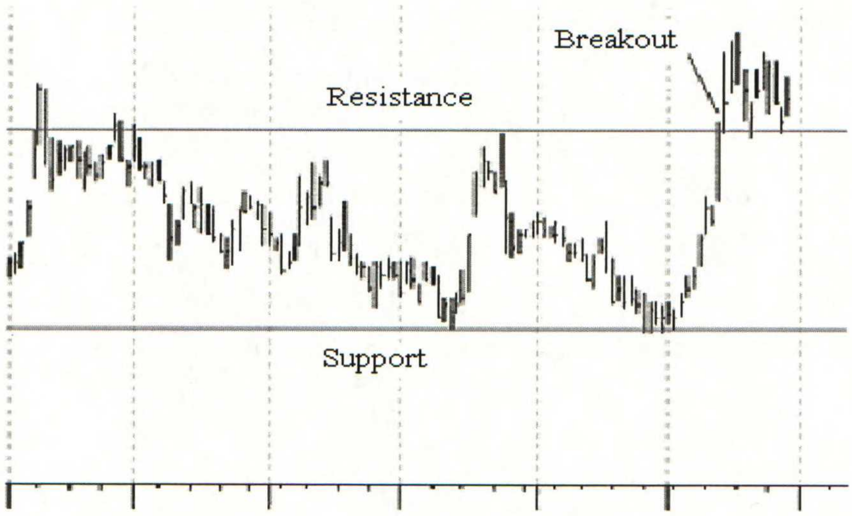

Figure 5 Exemplary support and resistance lines

The basis for support and resistance theories is that turnover in any given issue tends to be concentrated at the price levels where a large number of shares changed hands in times past. Theoretically, there is certain amount of supply and certain amount of demand at any given price level, but a support range represents a concentration of demand and a resistance range represents a concentration of supply (Edwards 1992). There also are certain other levels, which may, at times, evidently produce considerable resistance or support without any special reference. A good example is the given by round figures like 20, 30, 50, 75, 100 (Edwards 1992).

[18] Net demand here means demand less supply.

Again, there are various ways to use the method for trading. According to one approach, trading should occur in a breakout of a trendline channel. However, it has been advised that in some cases, a breach of a trendline may not be a breakout, but indicates just the need to adjust the trendline.

Certain rule modifications don't even utilize the chart. For example, Sullivan et al. (1999) present a simple mechanical rule based on S&R. The buy indication is given when the closing price exceeds the maximum price over the previous n days, and the sell when the closing price is less than the minimum price over the previous n days.

It has been stated that often after the penetration of a support or resistance level traders question the new price levels. For example, after a breakout above resistance level, buyers and sellers may both question the validity of the new price. After this the consensus of expectations can be that the new price is not warranted, in which case the price is assumed to move back to its previous level. Alternatively, investors will accept the new price, in which case prices will continue to move in the direction of the penetration. It has been also suggested that when a resistance level is successfully penetrated, the level often becomes a support level. Similarly, when a support level is successfully penetrated, it becomes a resistance level.

Also other charts than line charts are used to identify support and resistance levels. For example, as point & figure charts record only price movements exceeding specified levels, they have been honored for being suitable for detecting support and resistance levels and related breakouts.

5.3.3 Price Patterns

The price patterns are literally recognized patterns in chart illustrating the price data development. These can be divided in two main categories. *Reversal* formations forecast the trend turn and the *continuation* formations forecast the trend continuity. The main patterns indicating the trend turn are Head and Shoulders, Triangles, Saucer, Broadening formations, One day reversal, Key reversal day and Island reversal. The main patterns indicating the trend continuity are Flag, Pennant and Wedge, Gaps and Long Base formation.

One of the most well-known ones is Head and Shoulders that is described below as an exemplary price pattern. It literally means a shape of head and shoulders like illustrated in the figure 6.

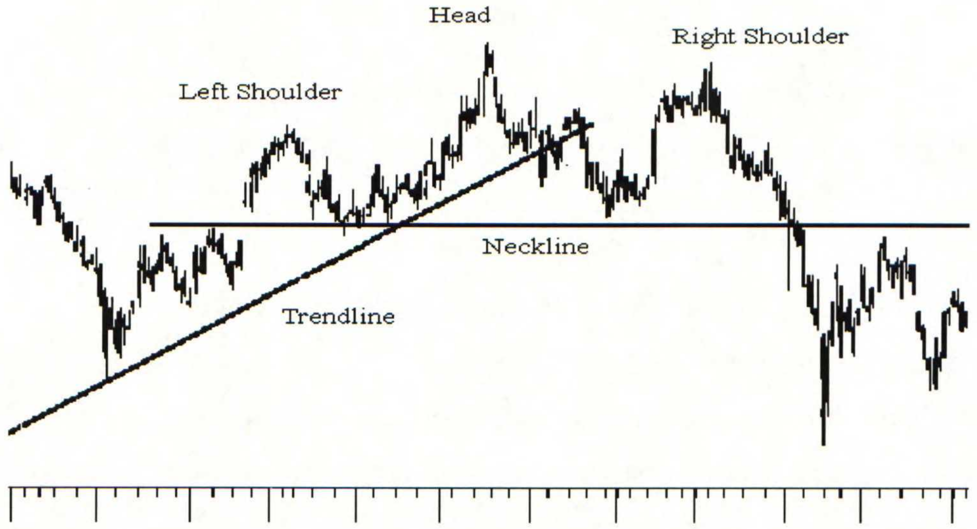

Figure 6 An exemplary head and shoulders pattern

The pattern is supposed to include a head and two shoulders. It is a major reversal pattern with four distinct features:

- Left shoulder is a top ensured by a minor reaction (fall) with significantly low volume.
- Head is another top reaching higher level than the left shoulder, ensured by another low volume reaction that takes the price to a level near the left shoulder bottom.
- Right shoulder is a third top that fails to reach the top of the head rally, ensured by a noticeably lower volume.
- The neckline is crossed when prices decline below the bottoms of the left shoulder and head. Neckline is also called support.

Head and shoulders and other reversal patterns should naturally provide investors the right time to sell and buy the shares. Consequently, it is important to notice that a head and shoulders pattern is not complete and uptrend is not supposed to be reversed until neckline support is broken. Ideally, this should also occur in a convincing manner with an expansion in volume.

Also other charts than line charts are used to identify chart patterns. On the other hand, these bring certain disadvantages. For example, in point & figure charts, patterns like key reversal days, islands and gaps do not show up (Pring 1991).

5.4 Filter Rules

Now the study concentrates on more mechanical analysis methods where trading decisions require less interpretations and no graphical analysis. Firstly, *filter rules* represent a more sophisticated version of trend analysis

Fama & Blume (1966) define the standard filter rule, an x% filter, as: If the daily closing price of a particular security moves up at least x%, buy and hold the security until its price moves down at least x% from a subsequent high, which indicates the time to sell the security. This position is maintained until the daily closing price rises at least x% above the subsequent low when it is time to buy again. Moves less than x% in either direction are ignored.

Filters have been honored to be an appropriate mechanical tool for filtering out the less-significant movements e.g. trendline breakouts. However, filter and other trend-following rules have been criticized for being late. The trend turn may be indicated only when the trend has already turned. With filter rule, the sensitivity can be improved by adjusting the abovementioned x value. On the other hand, filter rules are sometimes stated to generate even too frequent trades, which may generate large total transaction costs.

5.5 Moving Average

Moving average (MA) crossover rules, highlighted by Brock et al. (1992), are among the most popular and common trading rules discussed in the technical analysis literature. (Sullivan et al. 1999) Like mentioned previously in chapter 5.2, the method has been praised to provide profitable trading decisions especially when there exists a clear trend in the surveyed data series. However, this characteristic of trend following means that also MA rules usually reveal the change in the trend only when it has already turned, which has often criticized to be too late.

As MA is the first technical trading method employed in this study, this chapter lists only the principles behind the MA trading rules and calculation of most common different moving averages included in the rules. The rationale for the rule selection and the use of selected MA methods will be described in more detail later in the chapter 6.

Bodie et al. (1999) include speculation in their definition of MA method. They actually present two approaches for using MAs. On one hand, an average price over the past several months can be taken as an indicator of the "true value" of a stock. If current stock price is above this value, it may be expected to fall and vice versa. On the other hand, the moving average can be taken as an indicative of long-run trends. For example, if the trend has been downward and if the current stock price is below the moving average, then a subsequent increase in the stock price above the moving average line (a breakthrough) might signal a reversal of the downward trend.

Ratner & Leal (1999) see also the connection between the time series statistical properties and the principle behind the MA method. They define the moving average trading models to take advantage of positive serial correlation in equity returns. A trading signal usually follows a large movement in stock price under the assumption that the autocorrelation bias in the time series trend will continue in the same direction (Ratner & Leal 1999).

In general, most common use of MA trading rules includes calculating the moving averages and comparing these to a data point or another moving average. For example, according to the Variable Length Moving Average (VMA) rule[19], buy and sell signals are generated by two moving averages – a long-period average and a short-period average. In its simplest form this strategy recommends to buy (or sell) when the short-term average rises above (or falls below) the long-term average.

Different moving average trading rules follow this basic trading idea. However, the views on optimal trend recognition, and thus the ways the averages are calculated, are different. In practice, this means that there are different ways to assign the weight to data involved in average calculation.

The four most common types of moving averages used in technical analysis include simple (also known as arithmetic), weighted, exponential and triangular moving averages. Additionally, there exists a wide variety of other MA methods, but these are more rare and therefore not included in this summary. These four moving averages are described below in principle level, while the actual equations used to calculate the moving averages are listed in the appendix B.

The most common moving average is the *simple moving average (SMA)*, which applies equal weight to all values. Although this specific average calculation method usually has the abbreviation MA, in this study the abbreviation is replaced with SMA to differ the specific method from the general class of moving averages and MA trading methods. SMA can be calculated by summing a chosen number of subsequent values and dividing the sum with this chosen number.

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[19] The name originates from Brock et al. (1992) study.

The trading method including simple moving averages has been questioned because only the period covered by the average is taken into account and because SMA gives equal weight to each day's price (Murphy 1986). Consequently, the method including simple averages has been insisted to indicate a sharp rise or fall too late. To improve method performance, some analysts believe that a heavier weighting should be given to more recent price action (Murphy 1986).

Weighted moving average (WMA) is used and calculated like SMA but the days are weighted. For example a 10-day moving average could now be calculated by multiplying 10th day's price by ten, 9th day's price by nine, 8th day's price by eight etc. The sum of these is then divided by the sum of the multipliers. Now the latest data gets higher weight than the previous ones. However, the method still includes data only from certain time period.

Exponential moving average (EMA) also assigns a greater weight to the more recent action. But while it assigns diminished importance to past price action, it still includes in its calculation all of the price data (Murphy 1986). EMA is used like other moving averages, but the average is now calculated by multiplying the latest price with a fixed number w (between 0 and 1) and by adding this total to the previous exponential moving average, that is multiplied first with 1 – w.

Triangular moving average (TMA) is similar to exponential and weighted moving averages, except that a different weighting scheme is used to enhance smoothing. The middle values are weighted more than the early and late values.

5.6 Oscillator Analysis

Like moving averages, most of the technical analysis methods concentrate on following the trend. It has been insisted that, as a common characteristic, they usually reveal a change in the trend only when the trend has actually turned. However, in antitrending markets this is not enough. Consequently, more sensitive trading-range indicators, like oscillators, have been recommended.

As oscillators monitor price changes instead of price levels, they are assumed to indicate a trend change before this has actually happened (Nordin et al. 1989). The changes in oscillator values are simultaneous to the ups and downs in the price development. Sensitive indicators generate several signals, which brings also a greater risk due to the increased possibility for false signals and whipsaws. Therefore oscillators perform weakly on trending markets, but are ideal for complementing the trend-following rules and they have been stated to be especially useful in trading-range markets, like already mentioned in chapter 5.2.

Oscillators are utilized to determine when a market is in an *overbought* and *oversold* state. When an oscillator reaches the upper extreme, it is believed that a market has risen too far and is vulnerable to selloff. The market is said to be overbought. When an oscillator reaches the lower extreme, it is believed that the market has dropped too far and is due for a bounce. The market is now said to be oversold (Murphy 1991).

Also common trading systems utilize the interpretations of overbought and oversold markets. Depending on the selected system, an investor should be buying when the oscillator value is close to the critical overbought levels and selling when the value is close to the critical oversold levels. Also the zero or middle line breakthroughs are used to generate buy and sell signals.

There exist several different kinds of oscillators. According to Pring (1991) and Isakov & Hollistein (1999) the two most popular ones are the Relative Strength Index and the Stochastic Indicator. Technical analysis literature discusses also other common oscillators like Momentum, Price, Volume and MACD.

The basic application of oscillator analysis is called *momentum*. This is a method analyzing the speed of the price change. Momentum can be calculated as a difference or ratio of two moving averages with different lengths. (Nordin et al. 1989) Although moving averages are trend-following indicators, oscillators are assumed to give trading signals faster than the moving averages.

Also a specific oscillator is called *momentum*, which measures the positive or negative amount that a security's price has changed over a given time span. When it is used as a trend-following indicator, indicator peaks and bottoms should be used as trading triggers. But when it is used as a leading indicator, already the rapid price changes should be interpreted as trading signals.

Relative strength index (RSI) is a popular oscillator that is based on abovementioned momentum and moving averages. The oscillator measures internal strength of a time series by following the recent positive and negative fluctuations and their strength. As RSI is the second technical trading rule employed in this study, the rationale for the rule selection together with the use and calculation of RSIs will be described in more detail in the chapter 6.

Stochastic indicator (SI) is a short-term (2-4 weeks) measure of stock pricing. The stochastic indicator attempts to determine when prices start to cluster around their low of the day in an uptrending market, and when they tend to cluster around their high in a downtrending market. These are supposed to indicate trend reversals. When the stochastic indicator is at the top (bottom) of the chart, it indicates that prices are high (low) relative to recent history and it is time to sell (buy). In practice, the stochastic indicator is plotted as two lines and trading signals are translated from these.

Volume oscillator displays the difference between two moving averages of a security's volume. The longer-term moving average is subtracted from the shorter-term moving average. In general, the difference between the moving averages can be used to determine if the overall volume trend is increasing or decreasing. Still, there are many ways to interpret changes in volume trends.

MACD (Moving average Convergence/Divergence) is again a momentum indicator that shows the relationship between two moving averages of prices. The name of the indicator is derived from the fact that the shorter MA is continually converging toward or diverging away from the longer MA. It is calculated by subtracting the longer moving average from the shorter one. The resulting plot forms a line that oscillates above and below zero. Probably the most common MACD indicates the difference between a security's 26-day and 12-day exponential moving averages. Third, e.g. a 9-day exponential moving average is then plotted on top of the MACD as the *signal line*. The basic MACD trading crossover rule is to sell (buy) when the MACD falls below (rises above) its signal line. It is also popular to buy/sell when the MACD goes above/below zero.

Price oscillator is almost identical to MACD, except that the price oscillator can use any two user-specified moving averages and the difference between the moving averages can be expressed in either points or percentages. Also the moving averages used to calculate the price oscillator can be exponential, weighted or simple.

6 METHODOLOGY

The target of this research is to estimate the weak form efficiency of Budapest Stock Exchange (BSE), Prague Stock Exchange (PSE) and Warsaw Stock Exchange (WSE) by first evaluating the time series with statistical methods and later by estimating whether it is possible to achieve abnormal profits in these stock exchanges.

The data potential for profitable technical analysis is first estimated by evaluating the statistical properties of the time series. This means surveying the data stationarity, autocorrelation and runs. The possibilities to gain abnormal profits are then estimated by employing the selected technical analysis methods and comparing the simulated trading results to the buy & hold strategy profits. The selected technical analysis tools are trading rules based on moving average (MA) and relative strength index (RSI). This trading performance is measured with absolute and risk-adjusted figures i.e. Sharpe measures.

This chapter presents the methodology in more detail. First the selected technical analysis methods and the general trading principles are described. After this the statistical methods are introduced. In addition to presenting the tool and parameter selection the discussion concentrates also on reasoning the selections.

6.1 Basis for Trading Rule Selection

6.1.1 General Guidelines

The trading rule selection employed in this study is based on technical analysis literature and previous studies. As the universe of different trading rules is enormous, the first selection has to be made in more general level and is based on different market conditions and the suitability of different market structure indicators for each type of markets. Like mentioned in chapter 5.2, e.g. Pring (1991) divided the market conditions in trending and trading-range ones and consequently also the market structure indicators were categorized in respective classes. A trending market should be ideal for trend-following systems, but if there is no clear trend in the market, it has been suggested that the employed method should be one of the trading-range indicators.

However, it is difficult to define this market characteristic beforehand. It is actually impossible to classify markets in completely trending and antitrending ones as usually they include characteristics of those both. For example, when a clear trend is disappearing in a trending market, it has been claimed to be common that there exist some horizontal movement before a new clear trend can be found. Consequently, both a trend-following and a trading-range indicator will be selected for analyzing the time series in this study.

Now the indicators should be defined in more detail. To give results comparable with previous studies and to avoid the data-snooping bias, this research employs mainly methods that have been used in previous studies. Further, this thesis tries to employ simple methods insisted to be used by the investors, which should assist in simulating the investment process of an average investor.

6.1.2 Trend-Following Rule

First, the trend-following indicator is chosen. As mentioned in the chapter 2 browsing the previous studies, the moving average (MA) crossover method has been applied in several studies like the ones by Brock et al. (1992), Bessembinder & Chan (1995 and 1998), Hudson et al. (1996), Ready (1997), Ratner & Leal (1999) and Sullivan et al. (1999). For example, in the Brock et al. study, the method selection has been reasoned with the idea, that the rule is one of the simplest and most widely used technical trading rules.

Consequently, the first analysis method selected for this research in MA. In more detail, as the previous studies have used VMAs employing two simple moving averages (SMA) in trading signal calculation, similar VMAs have been selected also for this study.

6.1.3 Trading-Range Rule

From trading-range indicators, oscillators have appeared as the most popular ones. For example, according to Nordin et al. (1989), the oscillators have been praised as they indicate the trend change before this has actually happened. Consequently, oscillator analysis is applied also in this study.

In more detail, from all oscillators relative strength index (RSI) is selected. This has been selected based on the method selection in studies like the one by Isakov & Hollistein (1999) and referring to the oscillator popularity, also mentioned in chapter 5.6. Still the RSI selection can't be reasoned as objectively as MA selection.

Some additional rationale for the use of RSI has been given by Welles Wilder, who introduced the oscillator and gave three arguments making it better than other oscillators:

1. When RSI is used, exceptionally high and low values are ignored. RSI filters out these high and low ends.
2. The value of the RSI indicator varies always between 0 and 100. Consequently, it is easy to point out the commodities with high volatility.
3. RSI is easy to calculate. When the first RSI has been calculated, only the price data from the following day is needed to update the RSI.

Although RSI is less affected by sharp rises or drops in price performance and it filters out some of the noise in trading data, it is also praised due to its sensitiveness.

6.1.4 Simultaneous Use of Several Indicators

After browsing the trading rules, it can be concluded that the use of any indicator has been criticized. The trend-following indicators are insisted to miss some characteristics of trading-range ones and vice versa. For example, according to Pring (1991) MAs are virtually useless in a trading-range market since they move right through the middle of the price fluctuations and almost always result in unprofitable signals. Oscillators, on the other hand, come into their own in a trading-range market. They are continually moving from overbought to oversold extremes, which triggers timely buy and sell signals. During a persistent uptrend or downtrend, the oscillator is of relatively little use because it gives premature buy and sell signals, often taking the trader out at the beginning of a major move. Also according to Eng (1988) the actual problem with moving averages is their inability to predict reversals. It leaves traders in the dark as to whether a price which breaks the moving average is really a reversal or just a false breakout.

However, e.g. according to Pring (1991), turning points in price trends are often preceded by divergences in the oscillators, so it may be a good idea to combine extreme oscillator readings with some kind of MA crossover. Also according to Eng (1988), oscillator techniques may either be used on their own or in conjunction with more "positional" techniques such as moving averages. In other words, the oscillators and moving averages actually tend to complement each other. The latter pays attention to where the price is and where it is coming from but gives few clues as to what specific changes mean or when direction will really be changed. Oscillators, on the other hand, may tell little about specific location of prices on a chart or how these locations tie together but they will tell when to expect a probable change in direction.

The cons of oscillators are highlighted and simultaneous use of different strategies is supported also by Nordin et al. (1989), who write that oscillators may occasionally provide erroneous signals. Due to these signals it is important to wait until the actual trend direction has changed. Therefore, they are seen mainly as secondary tools to be used with the trend analysis.

Consequently, the simultaneous use of trend-following and trading-range indicators has been recommended. According to Pring (1991), this is not assumed to result in a perfect indicator, but it might help to filter out some of the whipsaws.

Consequently, the selected technical trading rules to be applied in this study are moving average (MA) and Relative Strength Index (RSI), but also a combination of these rules giving trading signals only when both rules give equal signals.

6.2 Trading

6.2.1 Parameter Selection and Trading With Moving Average

The applied moving average rule is variable length moving average (VMA) also applied in several previous studies, e.g. in the Brock et al. (1992) one, and in the following studies replicating the same methodology. According to the VMA rule, buy and sell signals are generated by two simple moving averages (SMA) i.e. the ones calculated on a long period (L) and a short period (S).

Before expressing the moving average rule in more detail, it is modified by introducing a band (B) around the moving average. According to Brock et al (1992), the idea behind the use of bands is to avoid noisy signals and to be sure that a trend is really initiated. When the distance between the short and long moving average is less than a certain band (e.g. 1 percent of the long moving average), it is considered that the relative positions of moving averages cannot give reliable indications regarding the existence of a trend in stock prices (Isakov & Hollistein 1999).

Trading with variable length moving average rules means simply the comparison of the averages. Referring to Bessembinder & Chan (1998), buy (sell) signals are emitted when the short-term average exceeds (is less than) the long-term average by at least a pre-specified percentage band. A VMA (S, L, B) rule emits buy (sell) signals when the S-day moving average of prices exceeds (is less than) the L-day moving average of prices by at least B. With an equation, a *buy* signal can be expressed as:

$$\frac{\sum_{T-S}^{T} p_t}{S} > \frac{\sum_{T-L}^{T} p_t}{L} + B = Buy, \qquad (2)$$

where p_t = the daily price, S = number of days on the short period and L = number of days on the long period while B represents the trading band.

Respectively, a *sell* signal can be written as:

$$\frac{\sum_{T-S}^{T} p_t}{S} < \frac{\sum_{T-L}^{T} p_t}{L} + B = Sell. \tag{3}$$

The rule selection still requires the choice of parameters S, L and B. Pring (1991) mentions that MA parameters should be selected carefully due to incorporated risk, since MA is seen as a trade-off between volatility and sensitivity. The short-term MA may whip around and the chances of unprofitable signals are much greater. On the other hand, if the maximum distance between MA and current price is considered as the maximum risk, a longer-term MA may offer a larger maximum risk but fewer whipsaws.

However, according to Sullivan et al. (1999), while numerous variations of MA rule are used in practice, few of the original sources for the technical trading rules report their preferred choice of parameter values.

As Bessembinder & Chan (1998) try to avoid compounding the dangers of data-snooping biases by evaluating precisely the same set of technical trading rules as Brock et al. (1992), this is seen as an appropriate criteria to be applied as well in this study. Consequently, also MA parameter selection is copied from previous research implemented by Brock et al. (1992). This is completed with some modifications praised by Ratner & Leal (1999).

The selected MA rules are (1,50,B), (1,150,B), (5,150,B), (1,200,B) and (2,200,B) where short averages have values of 1, 2 and 5 and long averages values of 5, 150 and 200. According to Brock et al. (1992) these all are also among the most popular ones.

Now also the appropriate trading band B should be selected. The Ratner & Leal (1999) study differs from Brock et al. (1992) one, that evaluates each rule with a trading band of zero and 1%. According to Ratner & Leal, a trading band of one standard deviation would generate less trades, be more cost effective and account for the differences in volatility more accurately than the 1% band. As a result, they employ a trading band of zero and one standard deviation.

Thus, also in this study each rule is tried with bands of 0, 1% and one standard deviation. This totals 15 moving average combinations.

The applied bands (B) included in the equations (2) and (3) are consequently

$$B_1 = 0 \tag{4}$$

$$B_2 = 0.01 \frac{\sum_{T-L}^{T} p_t}{L} \tag{5}$$

$$B_3 = \sqrt{\frac{\sum_{i=1}^{n} (p_i - \overline{p})^2}{n}}, \tag{6}$$

where n = number of data points in the time series (until the time T). In other words, the standard deviation is calculated from the complete historical time series data.

6.2.2 Parameter Selection and Trading With Relative Strength Index

RSI is a momentum oscillator that ranges between 0 and 100. The name *relative strength index* is slightly misleading as an RSI does not compare the relative strength of two securities, but rather the internal strength of a single security. A more appropriate name might be *internal strength index*. The name is also unfortunate as it is easily confused with other forms of relative strength analysis such as *relative strength charts* and *relative strength rankings*. Most other relative strengths are completely different techniques that e.g. involve more than one stock in the calculation.

Trading is usually based on following the oscillator value and comparing this to the levels of neutralization, which give the oversold and overbought conditions i.e. critical values that also define the correct times for trading. For example, when using the most common critical values of 70 and 30 (usually indicated with an expression 70/30), movements above 70 are considered overbought, while an oversold condition would be a move under 30. According to the simplest technique, the trading signals are caused by RSI levels crossing these critical values. An overbought market RSI falling below 70 would cause a sell signal and an RSI rising above 30 would give a buy signal.
RSI can be expressed as:

$$RSI_t = 100 - \frac{100}{1 + RS_t}, \text{ where} \tag{7}$$

$$RS_t = \frac{\text{Moving average of positive price movements during the selected period}}{\text{Moving average of negative price movements during the selected period}} \tag{8}$$

Before parameter selection, the use of trading rule should be defined. Like it can be noticed in the example above, the use of neutralization levels may differ. For example, an oscillator can be interpreted to give signals always when the direction changes in overbought/oversold section. However, this study follows the common mechanical approach with clear trading triggers. The trading signals are given by RSI values standing off the overbought/oversold section. The shares are bought when the RSI value rises enough to cross the oversold level and sold when then RSI falls below the overbought level.

Now the parameter selection can be done. For *calculating* the RSI values, the only parameter to be defined is the period length. However, two other parameters i.e. the previously mentioned levels of neutralization are needed also for *interpreting* the RSI. The most common critical values of 70 and 30 are often replaced with values further or closer each others. For example, even 90/10 and 50/50 rules exist. With the 50/50 rule, an oscillator value above 50 indicates that average gains are higher than average losses and confirms bullish signals, while a centerline crossover below 50 indicates that losses are winning the battle and confirms bearish signals.

In this study RSI parameter selection has been made more intuitively than with MA rules. Most common overbought and oversold levels 70 and 30 were recommended already by RSI inventor Welles Wilder while some previous studies and other literature like Murphy (1986) use also levels 20 and 80. These four values have been selected also for this research.

The other parameter to be selected is the time period length i.e. the length of moving averages. Wilder originally employed a 14-day period, but according to Murphy (1986) technicians are experimenting also with other periods, such as 5- and 7-day spans. However, the shorter the time period, the more sensitive the oscillator becomes and the wider is the amplitude. Therefore also longer periods are sometimes employed, and to give an overall picture on RSI possibilities also in this study, these considerably short and long periods are now employed together with the traditional 14-day period. Finally, the final period selection is based on the study by Isakov & Hollistein (1999) who state that popular levels for the number of days are 5, 14 and 21. Consequently, this study uses 6 different RSI rules i.e. 70/30 and 80/20 RSI rules with 5-, 14- and 21-day periods.

6.2.3 Trading With Combination Rules

Like mentioned earlier, the simultaneous use of trend-following and trading-range indicators has been often recommended. For example, combining signals from extreme oscillator readings with some kind of MA crossover has been assumed to help to filter out some of the oscillator whipsaws.

In this study the combined rules consist of the previously mentioned MA and RSI rules. Each of the applied fifteen MA rules is tried together with each one of the six RSI rules meaning 90 different combinations. A trading decision is made only when the latest trading signals, given by both rules, are the same. A trading signal has been considered to be valid as long as the rule provides an opposite signal. For example, when the applied RSI rule gives a buy signal, the shares are bought only if the latest signal given by the applied MA rule advised to buy.

6.2.4 General Trading Principles

In this study, the trading signals are generated by the abovementioned rules. This chapter describes the assumptions and principles that have been needed to implement the simulations and to simplify the survey. First, the common ones, included in all the simulations, are presented.

1. The actual research i.e. the decision rule formation and the appropriate statistics collection has been implemented with Excel application.
2. The trading signals are calculated with previous day's close prices. Therefore, a trading decision can be seen to be made during the night i.e. after the exchange has closed and before the market opens in the next morning.
3. The securities are bought and sold in the beginning of each day with previous day's close price. In other words, the open price at time t is considered to equal the close at time t-1.
4. The trading has been done with and without transaction costs. The employed transaction cost levels are 0.5%, 1.0%, 1.5%, 2.0%, 2.5%, 3.0% and 3.5%.
5. The trading signal calculation does not take transaction costs into account i.e. an investor is not assumed to include transaction costs in decision making.
6. If there has been no trading on a certain day, the previous close price has been used as the current price.
7. Taxes are ignored. In other words, an investor is considered to be a market participant that does not need to pay the taxes.

8. Previous studies have used different tools to invest the money that is not invested in a primary investment i.e. in a share, index or portfolio. The money in these secondary investments either generates no profit or some profit e.g. according to certain interest rate. Therefore this study uses three different scenarios. When the money is not invested in shares etc., it is either
    - Not invested at all, which generates 0% profit.
    - Invested with 2% annual interest rate, which is assumed to reflect the return rate of a tax-free bank account.
    - Invested in a tool reflecting the changes in a respective market index.
9. The money invested in a primary investment, i.e. share, index or portfolio, can be used only for this particular primary investment or the applied secondary investment.
10. The portfolio values are calculated every day assuming that all the profits are accrued daily.
11. All transactions are assumed to happen immediately. In other words, the study does not simulate the time it takes to make the actual transaction. In reality, already the lag time between the moment the shares are sold and the moment the money has been received is usually between 2-5 days. Therefore, e.g. in the case of a sell decision, the investor is assumed to sell the shares etc. and simultaneously simply invest in a secondary investment tool an amount that equals the sold position deducted with possible transaction costs.
12. The dividends, splits and issues are taken into account in investment values. Possible profit is calculated immediately as daily profit.

In addition to these assumptions, trading with MA rules required the following simplification:

13. Due to the use of close prices, this study applies $p_{i,t}$ in both moving averages. Some researches have used $p_{i,t-1}$ when calculating the long average, but this study assumes the investor to be able to use the latest close prices as current prices i.e. to buy and sell early next day with the previous closing prices.

Additionally, trading with RSI rules required the following simplification:

14. When calculating the RS in RSI trading rule, the nominator cannot be zero. Therefore, although the moving average of negative price movements has been zero, a moving average value of 0.01 has been used instead.

6.3 Statistical Testing

In addition to technical analysis, market data is tested with different statistical methods. The purpose is to evaluate the randomness of subsequent price movements as non-randomness may indicate predictable patterns in time series and thus possibilities for profitable technical analysis. In this study the predictability is measured with autocorrelation multiples and runs tests.

On the other hand, to be able to analyze autocorrelations and runs correctly, the time series stationarity should be first evaluated. Consequently, the statistical testing is started with stationarity tests.

6.3.1 Stationarity

6.3.1.1 Definitions

As model development for time series begins, it would be nice know whether or not the underlying stochastic process that generated the series can be assumed to be *invariant with respect to time*. If the characteristics of the stochastic process change over time, i.e., if the process is *non-stationary*, it will often be difficult to represent the time series over past and future intervals of time by a simple algebraic model. On the other hand, if the stochastic process is fixed in time, i.e., if it is *stationary*, then, it is possible to model the process via an equation with fixed coefficients that can be estimated from past data. (Pindyck & Rubinfeld 1982)

The expression *invariance with respect to time* includes the characteristic that a stationary series has a constant mean and a constant variance over time. The differences between stationary and non-stationary time series include also the fact that shocks to a stationary time series are necessarily temporary; over time, the effects of the shocks will dissipate and the series will revert to its long-run mean level. As such, long-term forecasts of stationary series will converge to the unconditional mean of the series (Enders 1995).

To illustrate some of the issues involved, a first-order stationary time series can be expressed as:

$$y_t = a_1 y_{t-1} + \varepsilon_t, \qquad (9)$$

where y_t = the value at time t, a_1 = first-order slope coefficient, y_{t-1} = the value at time t-1 and ε_t = a random value around the average at time t.

6.3.1.2 Estimating Stationarity

There are several methods for stationarity testing. The one applied in this study is called Dickey-Fuller test.

As the existence of a unit root indicates the time series to be non-stationary, Dickey-Fuller and augmented Dickey-Fuller tests evaluating the presence of a unit root can be used to estimate the stationarity. These tests can also be used to help detecting the presence of a deterministic trend (Enders 1995). Dickey & Fuller (1979) actually consider three different regression equations that can be used to test for the presence of a unit root:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{10}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \varepsilon_t \tag{11}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \varepsilon_t \tag{12}$$

The test involves estimating one (or more) of these equations using OLS in order to obtain the estimated value of γ and associated standard error. (Enders 1996)

The difference between the three regressions concerns the presence of the deterministic elements a_0 and a_2t. As an interpretation, the first is pure random walk model, the second adds an intercept or drift term, and the third includes both drift and linear time trend. However, the methodology is precisely the same regardless of which of the three forms of the equations is estimated. The parameter of interest in all the regression equations is γ; if $\gamma = 0$, the $\{y_t\}$ sequence contains a unit root. Consequently, the hypotheses are:

H_0: $\gamma = 0$

H_1: $\gamma \neq 0$

The null hypothesis means that the $\{y_t\}$ sequence is generated by a non-stationary process. Under the null hypothesis, it is inappropriate to use classical statistical methods to estimate and perform significance tests on the coefficient a_1 found in the equation (9).

6.3.1.3 Test Employed in the Study

In practice, the Dickey-Fuller test can be implemented e.g. with Excel. According to Kanto (2003) an accurate Dickey-Fuller test can be easily implemented with a regression analysis, where regression between price change and delayed series is calculated. This equals testing the equation (11) with an intercept term but without a trend term.

The acceptance or rejection of the null hypothesis $\gamma = 0$ can be determined by comparing the *t*-statistics resulting from the regression analysis with the appropriate critical values. For example, Enders (1995) reports these critical values as the Empirical Cumulative Distribution of τ, reproduced from Fuller (1976). It can be seen in the table that, to compare the *t*-statistics to critical values, the table use requires the recognition of the sample size and the appropriate confirmation level. In this study

- The sample size is always regarded as infinite, because each sample size exceeds 500.
- 90% confidence level is used.

Now the *t*-values can be compared to the critical values. According to the table, with the infinite sample size, in the presence of an intercept, 90% of the estimated values of a_1 are less than 2.57 standard errors from unity. In other words, with *t*-values greater than -2.57 it will not be possible to reject the null hypothesis and the null of a unit root.

6.3.2 Autocorrelation

6.3.2.1 Definitions

While it is usually impossible to obtain a complete description of a stochastic process, i.e. actually specify the underlying probability distributions, the autocorrelation function is extremely useful in helping to obtain a partial description of the process for modeling purposes. The autocorrelation function provides a measure indicating how much correlation there is (and how much interdepency there is) between neighboring data points in the series. (Pindyck & Rubinfeld 1982)

Like mentioned earlier, for this study, estimation of autocorrelation offers a possibility to evaluate the time series randomness and to reveal the possibilities for successful trading and the possible market inefficiencies. In practice, the observations should move in same or opposite directions systemically so that technical analysis is also theoretically the method to be used for profitable trading.

6.3.2.2 Estimating Autocorrelation

As the evaluated data series are still samples, the sample autocorrelation has to be calculated. The equation for calculating the sample autocorrelation with lag k can be expressed as

$$\hat{\rho}_k = \frac{\sum_{t=1}^{T-k}(y_t - \bar{y})(y_{t+k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2}, \tag{13}$$

where y refers to the daily value. For example, with lag four the variables are y_t and y_{t+4}. The calculated autocorrelation is the correlation between these values.

In the case of stationary time series, to properly check the model autocorrelation, the residuals[20] should be also surveyed. The residuals will most probably be stationary, but autocorrelation may have disappeared. When there exists no autocorrelation in residuals, they should be independent on each value of the variable. If also the residuals indicate significant autocorrelation, the series can be considered as an autocorrelated one.

Also non-stationary data can be used as a stationary one e.g. a possible trend can be removed. A special type of filtering, which is particularly useful for removing a trend, is simply to difference a given time series until it becomes stationary. First-order differencing is also now widely used in economics. (Chatfield 1984)

Also Pindyck & Rubinfeld (1982) conclude that many of the non-stationary time series encountered (and that includes most of those that arise in economics and business) have the desirable property that if they are differenced one or more times, the resulting series will be stationary.

The statistical significance of autocorrelation multiples is tested with a test statistic calculated with the data. When the multiple is significantly different from the value zero, autocorrelation is assumed to exist. Still, there are different test statistics indicating the statistical significance of the autocorrelation and they may give different results.

6.3.2.3 Test Employed in the Study

Autocorrelation is tested with SPSS application. In addition to the original time series, with non-stationary time series also the stationarity of first-order differenced series is evaluated. When a series is proved to be a stationary one, also residuals are measured. The only parameter to be selected for autocorrelation testing is the maximum lag employed, which in this case is 25.

Also the statistical significance of the autocorrelation multiples is tested with test statistics calculated from the data. A simple method to evaluate autocorrelation is Box-Pierce Q-statistic.

$$Q = n\sum_{i=1}^{k} r_i^2, \tag{15}$$

where n = number of observations, k = maximum lag size and r_i = an autocorrelation with lag i. Using an appropriate degree of freedom and confidence level the χ^2 distribution can be explored to check the P-values indicating the autocorrelation significance. The degree of freedom equals the number of lags used in the statistic subtracted with the number of fitted parameters other than a constant term. In this study the number of lags is 25 and 1 estimated parameter decreases the degree of freedom to 24.

6.3.3 Runs Tests

6.3.3.1 Definitions

It has been stated that stock market researches concentrating only on autocorrelation analysis may include a bias that should be corrected or at least highlighted with other methods. This weakness of correlation researches has been pointed out e.g. by Berglund (1986) who states that the main reason why correlation coefficients estimated on stock returns may be misleading is that the frequency distribution for stock returns is fat-tailed in comparison with a normal distribution. The reason why this may cause problems is that extreme returns may dominate the results. Thus two extreme returns that by chance happen to arise on adjacent trading days may create an erroneous impression of an underlying relationship.

A commonly used method in trying to avoid the statistical problems created by non-normal, in fact unknown, return distributions is to use non-parametric statistics. When non-parametric methods are

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[20] Residuals are the differences between observations and fitted values.

applied, the underlying return generating probability distribution is of no consequence for the results. The reason for this is that the attention is focused exclusively on the sign of the return, i.e. whether it is negative, zero or positive. This is also the drawback of non-parametric as compared with parametric methods; Important available information, i.e. the magnitude of the reasons is in fact left unused. This makes non-parametric methods less powerful than their parametric counterparts. Therefore, after hesitating which method to use, a common solution is to apply both methods to see whether the conclusions agree or disagree. (Berglund 1986)

One test for independence between successive returns, which does not require normality, is the runs test. This non-parametric test is commonly applied to examine independence of stock returns further. Also in this study the complementary test for randomness is implemented with runs test.

The basic idea of runs tests is to determine if there are any patterns or trends in the plotted points e.g. price changes. In more detail, the runs test procedure tests whether the order of occurrence of two values of a variable is random by detecting the frequency of the changes in the direction of a time series.

Runs tests apply to data in which elements are ordered and may belong to two or more categories, which can be e.g. the price movements below and above median change. A run is formed by consecutive events of the same kind.

A sample with too many or too few runs suggests that the sample is not random. The statistical basis of the runs tests is simply that if the subgroups are truly from the stated distribution, and independent of one another, then there will not be any pattern in the points.

6.3.3.2 Implementing the Test

Runs test can be implemented with following steps:

1. The data is divided in different categories according to applied cut points that can be e.g. data median, mode or mean. Exemplary categories could be then the price changes above and below the median etc. If more than two categories are used, the categorization is often based on quartiles.
2. The runs are formed. Consecutive events of the same kind i.e. in the same category constitute a run, where the number of consecutive events is irrelevant.
3. The runs formed in different categories are then coded with characters, e.g. numbers.

4. The time series properties are finally evaluated with the standard normal variable Z. For example, if there are two categories 1 and 2, and data will be categorized to price changes above and below the median, the Z value, determining if the runs of price changes above or below the median price are significant, can be calculated with the following equation (Sherry 1992):

$$Z_{12} = \frac{N(R-1/2)-2n_1n_2}{\sqrt{\frac{(2n_1n_2)(2n_1n_2)-N}{N-1}}} \tag{16}$$

where N = the total number of price changes, R = the number of runs and n_i = the number of data involved in runs of class i.

Under the hypothesis of independence, the distribution of the total number of runs is approximately normal. (Urrutia 1995) Therefore, if the value of Z falls between -1.96 and +1.96, the number of runs could have occurred by chance alone. If Z is outside this range, the time series data is not normally distributed (Sherry 1992). In this case the number of runs probably did not occur by chance alone; that is, a deterministic process may be at work. If this is true, the rules that make this process work may be determined and this information can be used to make better trading decisions.

Again, in the case of a stationary time series, to double-check the runs test results, the residuals should also be surveyed. If the Z value of the residuals is outside the range, the randomness can be finally rejected.

Respectively, in the case of a non-stationary time series, the series is differenced to make it stationary and applicable for further forecasting and testing. Therefore, the runs tests have been employed also for differenced time series.

6.3.3.3 Test Employed in the Study

The runs tests have been implemented with SPSS application. Again, mandatory assumptions have to be made before conducting the actual analysis. This includes defining the number of different categories and the cut point dividing the data in these categories.

The most common and simple analysis with two categories is used. The selection is based on the features of SPSS as the application allows the use of only two categories.

Also the most common cut point i.e. median is selected. Consequently, this study conducts a runs test for price changes that have been divided in two different classes, the price changes below and above median. This is also the SPSS default.

6.3.4 Discussion on Statistical Testing

Statistical testing and especially autocorrelation researches have been discussed widely in previous studies. Already Fama & Blume (1966) criticized the use of certain methods in market efficiency evaluation. As it has been generally accepted, they stated that the existence of autocorrelation in financial markets does not necessarily imply market inefficiency. They saw no obvious relationship even between the magnitude of a serial correlation coefficient and the expected profits of a mechanical trading rule.

Statistical testing has been also argued to be useless for technical analysis. According to Fama & Blume (1966), the market professional would probably object that common statistical tools cannot measure the types of dependence that he sees in the data. For example, the simple linear relationships that underlie the serial correlation model are much too unsophisticated to identify the complicated patterns that a chartist sees in stock prices. Similarly, runs tests are too rigid in determining the duration of upward and downward movements in prices. A run is considered terminated whenever there is a change in sign in the sequence of successive price changes, regardless of the magnitude of the price change that causes the reversal in sign. A market professional would require a more sophisticated method to identify movements – a method that does not always predict the termination of the movement simply because the price level has temporarily changed direction.

Also the origin of correlation is discussed in previous studies. According to Urrutia (1995), some researchers suggest that government intervention policies may cause stock price changes to be positively correlated. Spurious positive autocorrelation may also be due to infrequent or nonsynchronous trading that can introduce large trading errors. Poterba & Summers (1988) indicate that stock index returns may show positive autocorrelation if some of the securities in the index trade infrequently. They argue that small stocks trade less frequently than larger stocks. Therefore, new information is incorporated first into larger stock prices and then into smaller stock prices with a lag. This lag induces a positive serial correlation. Finally, noise trading - that is, trading by investors whose demand for stocks is determined by factors other than their expected return - may also provide an explanation for transitory components in stock prices. (Urrutia 1995)

6.4 Measuring Performance

6.4.1 Different Indicators

Before conducting the research, this chapter first discusses briefly the different performance measuring indicators that can be used when evaluating the results obtained with technical trading rules. Naturally, after investing, the focus usually is in the profit gained. However, it has been insisted that returns should be adjusted for risk before they can be compared meaningfully.

According to Bodie et al. (1999), the simplest and most popular way to adjust returns for portfolio risk is to compare rates of return with those of other investment funds with similar risk characteristics. However, they suggest that there are more precise means for risk adjustment. Consequently, the three classic and most common measures of risk-adjusted portfolio performance, i.e. measures of Sharpe, Treynor and Jensen, are presented.

Sharpe measure is a reward-to-volatility ratio that can be used to standardize the returns of any portfolio. In more detail, Sharpe measure tells you how much return the portfolio provided given its risk. Consequently, the Sharpe measure can be used to compare an investment to market portfolio or any two other investments to each other.

Treynor measure is similar to Sharpe measure, but while Sharpe uses total risk, Treynor ratio equation includes only the variation that is correlated with the entire market. In other words, the denominator has systematic risk measure beta, which represents the estimated change in the return of the investment for one unit change in the return of the market index.

Jensen measure is just the portfolio's alpha from capital asset pricing model[21]. Jensen measure is another way of telling the excess return of an investment. Like Treynor, it deals only with systematic risk. However, while Sharpe and Treynor calculate a ratio, Jensen measure is in linear form.

It has been stated that when one comprehensive strategy is compared to another, Sharpe measure is the appropriate one. However, if some of the money would be used to eliminate any firm-specific risk of comprehensive investments, the only interest lies in the systematic risk of those investments since the unsystematic risk will be diversified away. In this case, the Treynor measure would be more appropriate. (http://www.public.iastate.edu/~chatcher/583teaching/Unit11pg2.html)

The risk-adjusted performance measures have also been employed in previous researches. For example Sullivan et al. (1999), in addition to profits earned, used Sharpe measure to compare the results of active trading strategies. Therefore, also in this research, the technical trading rule performance is evaluated with monetary profit and Sharpe measure. Sharpe measure will be explained in more detail in the following chapter.

6.4.2 Sharpe Measure

As mentioned above, also risk-adjusted performance measures can be applied when evaluating the performance of a portfolio. The reward-to-variability ratio referred frequently in the active portfolio management is called Sharpe measure. This can be expressed as:

$$S = \frac{E(r_P) - r_f}{\sigma_P}, \tag{17}$$

where $E(r_p)$ = the expected return of portfolio p and r_f = risk free rate of return during the same period while $E(r_p) - r_f$ = the risk premium on p. Portfolio risk is measured with standard deviation σ_p. In other words, the measure compares the investment's reward to its risk by dividing the premium with standard deviation and resulting Sharpe can be interpreted as excess return unit per risk.

[21] Capital asset pricing model (CAPM) assumes that, in a competitive market, the expected risk premium varies in direct proportion to beta. When alpha is included, the model can be expressed as $r_p - r_f = \alpha_P + \beta_P(r_M - r_f)$, where α_P = the abnormal return of the active portfolio relative to the market index.

The measure can be used to standardize the returns of any portfolio and to compare different portfolios to each other. Consequently, it has also been argued to be a common criterion for tracking performance of professionally managed portfolios (Bodie et al. 1999). When portfolios are compared, an investment with higher Sharpe is considered to have succeeded better although the monetary profit was lower. Respectively, if the portfolio's Sharpe measure exceeded the market portfolio's Sharpe measure, the portfolio "beat the market."

In this study the data points are daily values and the calculated Sharpe measures would refer only to daily profits and standard deviation. Therefore, to be able provide more commonly used annual figures, the Sharpes calculated with daily values are converted with a multiple $365/\sqrt{365}$. Additionally, to be able to calculate the risk premium, r_f i.e. an appropriate risk free rate of return is needed. The applied annual rate in this study is 2.463%, which was the 12-month Euribor in the end of the research period in March 2003.

7 THE DATA

The data consists of trading information of thirteen shares and three major indices of Budapest Stock Exchange (BSE), Prague Stock Exchange (PSE) and Warsaw Stock Exchange (WSE). The markets have been selected based on the following criteria:

1. The interest lies in emerging and especially in less-researched East European markets. According to rationale presented below in chapter 7.1, all these three markets can be referred as emerging ones.
2. From all East European countries, Hungary, Czech and Poland are all under transition. Although they can be ranked as emerging markets, they are simultaneously OECD countries and members of European Union.

To reason the market selection, the categorization in developed and emerging markets will be discussed now in more detail. After this the major characteristics of selected three exchanges are presented. This will be followed by the introduction of the actual data i.e. the shares and indices included in the research.

7.1 Emerging Markets

7.1.1 Characteristics

Classification in developed and non-developed i.e. developed and emerging capital markets is used with certain rationales. There are some characteristics that are expected to be found in developed markets and some that can be found in emerging markets. For example Harvey (1995a), in his study surveying 20 new equity markets in emerging economies, pointed out that emerging markets have high average returns, low overall volatility, low exposure on world risk factors, and little integration in global economy.

Like mentioned in chapter 2.2.2 Harvey (1995b) also found that the autocorrelation in emerging markets was much higher than in developed markets. He also suggested that the level of autocorrelation is directly associated with the size and the degree of concentration of the market.

Additionally, transaction costs are another factor that distinguish emerging from developed markets. Levich (2001) reports that surveyed average round-trip trading costs in the fourth quarter of 1999 were estimated at 0.90% in developed country markets, and 1.80% in emerging markets. In developed country markets, round-trip trading costs were lowest in France (0.53 percent) and highest in Ireland (1.73 percent). Simultaneously in emerging markets, round-trip trading costs were lowest in Brazil (0.88 percent) and highest in the Czech Republic (3.59 percent).

According to Levich (2001) the International Finance Corporation (IFC) has made a more thorough description after surveying characteristics of emerging markets. IFC uses income per capita and market capitalization relative to GNP figures for classifying equity markets. IFC classifies a market as emerging if one of the following conditions is fulfilled:

1. The ratio of investable market capitalization to GNP is low.
2. The market resides in a low- or middle-income economy.

IFC identified 81 such countries. In those 81 markets, equity markets were small in relation to their economies, with market capitalization at only 30-40% of GNP. In developed markets the figure was 70-80%. Although the required ratio of investable market capitalization to GNP was met, several markets still resided in a low- or middle-income economy. For example, in 1998 the World Bank defined high income per capita GNP as USD 9 361. (Levich 2001)

Other possible classification criteria, researched by IFC, include

1. Average market capitalization per firm
2. Market concentration
3. Settlement periods

First, IFC evaluates that the *average market capitalization per firm* in emerging markets is far smaller than in developed country markets. In emerging markets the 1999 figure was USD 117 million and in developed country markets USD 1 413 million. *Market concentration* is another statistic with wide variation across countries. When measuring the concentration, S&P compares the market capitalization of largest ten firms to the total capitalization. According to this measure, concentration in emerging markets varies between 30% and 60%. On the other hand, when defining the concentration, the International Federation of Stock Exchanges calculates how much of the total market capitalization is created by the largest 5% of all firms. According to this measure, concentration in developed markets varies between 55% and 85%. (Levich 2001)

Reported *settlement periods* for equity transactions are fairly uniform around the world. Many emerging markets stipulate settlement periods of T+3 days (e.g. Argentina, Brazil, Czech Republic, Jordan, Peru and Thailand), or T+2 days (e.g. Chile, Korea and Mexico), or even less. These compare favorably with the T+2 settlement cycle in Germany, T+3 in the United States and Japan, and T+5 in London. However, these figures mask differences in operational efficiency and the possibility of operational post-trade failures that confront emerging equity markets. (Levich 2001)

Also S&P provides survey information comparing settlement performance, safekeeping in regard to the collection of dividends, and operational risks across emerging market countries. While many emerging markets are improving, the survey gives the impression that operational inefficiencies are common and material in most emerging markets. (Levich 2001)

Additionally, according to Levich (2001), market turnover, measured by comparing the annual volume of trading to the market capitalization, varies substantially. Firstly, the turnover varies considerably between markets. But turnover could vary as well within a market. Greater liquidity is often a characteristic of a small number of high capitalization stocks.

Finally, it can be concluded that emerging markets are heterogeneous but generally differ from developed markets in some features such as size, liquidity, trading costs and operational efficiency.

7.1.2 Market Classification

Hungary, Czech and Poland have been often referred as emerging capital markets. According to Levich (2001), following previously mentioned criteria, the selected markets were classified as emerging in 2000. Similar classification has been presented also e.g. in the research conducted by Yuce and Simga-Mugan (2000).

To provide more up-to-date classification the most recent available data is compared to the IFC emerging market classification criteria mentioned above in the section 7.1.1. For example, in BSE the equity market capitalization at the end of 2002 was HUF 2 947 billion i.e. USD 13 557 million (with HUF/USD rate 0.0046). According to World Bank statistics, in Hungary the 2002 total GNP was USD 53 702 million, while the per capita figure was USD 5 280. This gives the equity market capitalization to GNP ratio 25.2%. Referring to the first IFC classification rule, Hungary can be considered as an emerging market. This is supported by the second classification rule as the per capita figure is not high enough to provide Hungary the high-income status. All the markets are evaluated similarly in the following table 1:

Table 1 Rationale for classifying the selected markets in developed and emerging ones
The first rule expects the ratio of investable market capitalization to GNP to be low enough. According to the second classification rule, the market is emerging if a market resides in a low- or middle-income economy. All the figures present the situation in the end of 2002.

	Equity market capitalization (figures in millions)			GNP (in USD)		Capitalization/ Total GNP ratio	Classified as emerging	
	In local currency	Rate	In USD	Total (in mil.)	Per capita		1st rule	2nd rule
BSE	2 947 200	0.0046	13 557	53 702	5 280	25.2%	Yes	Yes
PSE	478 038	0.0369	17 625	56 717	5 560	31.1%	Yes	Yes
WSE	110 565	0.258	28 526	176 616	4 570	16.2%	Yes	Yes

It can be seen in the table that also PSE and WSE markets can be classified as emerging ones based on both classification criteria. Other clear emerging market characteristics described above in chapter 7.1.1 are average market capitalization and concentration. The BSE, PSE and WSE figures are presented in the table below.

Table 2 Average market capitalization and concentration of BSE, PSE and WSE in 2002
Concentration is reported with two figures. First one is calculated with S&P method by comparing the market capitalization of largest ten firms to the total capitalization. The second one follows the method presented by International Federation of Stock Exchanges, that calculates how much of the total market capitalization is created by the largest 5% of all firms.

	Average market capitalization (figures in millions)	Concentration	
		10 largest	5% of the largest
BSE	USD 276.68	91.49%	49.83%
PSE	USD 223.29	81.14%	69.59%
WSE	USD 132.06	70.73%	73.17%

The table shows that average market capitalizations are closer to abovementioned levels representing emerging markets. However, as it can be seen, the concentration levels are extremely high especially when calculated with 10 shares presenting highest capitalizations. Concentration presented by 5% of the largest companies is smaller in BSE and PSE already due to the small amount of listed shares in these exchanges. In fact, in BSE this 5% means 2 shares, in PSE 2 shares and in WSE 11 shares.

7.2 Budapest Stock Exchange

7.2.1 History

The Commodity and Stock Exchange of Hungary was established in 1864 and it began its development after the political compromise of 1867. However, the great economic crisis of the early 1930s also hit Hungary, and the exchange was closed from summer 1931 to fall 1932. The exchange was closed again on 1948, when the communism started dominating Hungarian political system. As a result of the political and economic changes in the late eighties, the Budapest Stock Exchange re-opened its gates on June 21st 1990.

The recent market development in the forms of market volume and capitalization together with the amounts of listed shares is presented in the table below.

Table 3 The development of Budapest Stock Exchange since the year 1995
The market capitalization and turnover figures are in billion HUF.

	2002	2001	2000	1999	1998	1997	1996	1995
Amount of Shares	49	56	60	66	55	49	45	42
Market Capitalization	2 947,20	2 848,80	3 393,90	4 144,90	3 020,10	3 058,40	852,5	327,8
Market Turnover	1 513,72	1 385,68	3 417,04	3 431,33	3460,36	1436,36	245,27	43,64

Since 1995 the market volume was growing heavily until the year 1998. The figure was quite stabile for a few years and finally decreased by 50% to its current levels. The market capitalization increased first similarly, but the fluctuations have been relatively moderate since 1997. However, the amount of listed shares has been quite stable during these years meaning remarkable growth in company market values.

7.2.2 Current Operation

The opening hours of Budapest Stock Exchange are 8:30-16:30. The continuous equity trading hours are 9:00-16:30. Exchange day's schedule is described in appendix C.

On December 31st 2002 there were 49 equities listed on the exchange. All shares were traded on one market. In other words, inside BSE there are no different markets for shares with different characteristics.

As it can be seen in the table 2, presented in the chapter 7.1.2, the market is extremely concentrated. This can be seen also in market turnover. There are basically four liquid shares as the rest of the common stocks are traded with considerably lower volumes.

There are four indices followed in BSE: BUX, CESI, CETOP20, DWIX and RAX:

- BUX i.e. Budapest Stock Index indicates price fluctuations in the domestic stock market. A maximum of 25 equities may be included in the index basket. The equities in the index are weighted with market capitalizations of each share with certain limitations. As BUX is an index analyzed also in this research, it will be described in more detail later in the chapter 7.5.2.
- CESI i.e. Central European Stock Index indicates price fluctuations in the equity markets of 5 exchanges in the region. These are Budapest, Ljubljana, Bratislava, Prague and Warsaw. Only shares listed in the official categories of the exchanges[22], having the largest capitalisation and liquidity can be included in the CESI basket. The papers of the share funds and portfolio companies are excluded. The total participation of securities from one country may not exceed 50% of the total capitalisation of the basket, but in order to insure the representative nature of CESI, the aggregate capitalisation of the shares of each country must represent at least 60% of their own official markets capitalisation.

[22] Official categories of the exchanges include equities that can be purchased by foreign investors.

- CETOP20 i.e. Central European Blue Chip Index indicates price fluctuations of blue chip stocks of the exchanges in the region. These are again Budapest, Ljubljana, Bratislava, Prague and Warsaw. The basket includes 20 stocks and the maximum number of stocks from each exchange is limited to 7.
- DWIX i.e. Daiwa-MKB Treasury Yield Index indicates short term risk free yield conditions until maturity (for 3-, 6- and 12-month discount T-bills). This yield index shows the weighted average of average yields and quantities accepted at primary auctions.
- RAX i.e. BAMOSZ Equity Investment Fund Portfolio Index is a benchmark of performance of domestic equity investment funds. It is a capitalization weighted stock index including 13 stocks with highest market capitalizations. Only a single series from the same issuer may be included.

7.3 Prague Stock Exchange

7.3.1 History

Czech exchange started in the middle of the 19^{th} century trading corn and agricultural products in weekly markets. In 1871 financial resources were procured for the foundation and operation of the exchange. That Prague exchange originally dealt in both securities and all other types of merchandise. However, after World War I securities trading was the only product that effectively continued. In the period between World War I and World War II, the exchange was undergoing a boom, which was violently interrupted by the second war. After this, the door of the exchange did not open. The tradition of the Czech exchange business found its continuation only in May 1991. The new company, composed of eight banking houses, was transformed into an association that was later converted into Prague Stock Exchange joint-stock company. On April 6^{th} 1993, the first trading session took place on its trading floor.

The recent market development in the forms of market volume and capitalization together with the amounts of listed shares is presented in the table below.

Table 4 The development of Prague Stock Exchange since the year 1995
The market capitalization and turnover figures are in million CZK.

	2002	2001	2000	1999	1998	1997	1996	1995
Amount of Shares	79	102	151	195	304	320	1 670	1 716
Market Capitalization	478 038	340 251	442 894	479 650	416 202	495 681	539 242	478 634
Market Turnover	197 398	128 799	264 145	163 457	172 594	246 301	249 935	125 643

Since 1995 the market volume has been fluctuating heavily. The relative changes in market capitalization have been more moderate. No special trend can be determined through just browsing the figures. The amount of listed shares, however, has decreased substantially. The change is mainly caused by the major shifts in *Free* markets.

7.3.2 Current Operation

The opening hours of Prague Stock Exchange are 7:30-20:00. The continuous equity trading hours are 9:30-16:00. Exchange day's schedule is described in appendix C.

On December 31st 2002 there were 79 shares listed in the exchange. 5 of these were listed on the *Main market*, 41 on the *Secondary market*, none on the *New market* and 33 on the *Free market*.

Assigned to *Main market* are the most liquid securities that are traded in the exchange. The Main market was officially established on September 1st 1995, upon the change in the concept of the markets existing at that time. The original classification for Listed and Unlisted markets was now removed and the Listed market was divided to the Main and Secondary markets.

The difference between *Secondary market* and Main market consists of the admission requirements that are less strict in Secondary markets. In more detail, the value of the public offer part of the issue for companies and the amount of registered capital (in the case of unit funds, value of unit issue) for investment funds and unit trusts required in Secondary markets need to be only half of the respective amounts in Main markets.

New market is an organic part of the Secondary market. The principal objective for setting the conditions suitable for the creation of the New market was to enable companies which, although may have a short history, have a prospective business objective to raise financial resources.

Unlike the other markets, *Free market*, originally the Unlisted market, is designed for issues, the issuers of which do not have to provide the exchange with such a quantity of information as the issuers of the other prestigious markets of the exchange.

As it can be seen in the table 2, presented in the chapter 7.1.2, the market it extremely concentrated. This can also be seen in the market turnover. There are basically five liquid shares as the rest of the common stocks are traded with considerably lower volumes.

There are 22 indices in PSE: PX 50, PX-D, PX-GLOB and 19 sector indices:

- In the Prague Stock Exchange the oldest and most famous one is the official index PX 50. This is based on a maximum of 50 issues selected because of their high market capitalisation and liquidity and taking into account of their sector classification. Investment fund issues are not included. As PX 50 is an index analyzed also in this research, it will be described in more detail later in the chapter 7.5.2.
- PX-D is used as an underlying asset for derivatives trading. The number of the base issues is variable. Issue's weighting is given by its share in market capitalisation. Share of market capitalisation allowed for one issue in the total market capitalisation of the base may not exceed 35%. Investment funds are excluded from the base.
- PX-GLOB is a global index, which encompasses all listed stocks and investment fund shares that have been traded at least once. Issue's weighting is given by its share in total market capitalization while the calculation formula is the same as in PX 50.
- Additionally, there are 19 sector indices of sectors in which the number of constituents has not dropped below three. Out of these indices only 11 had more than three constituents in the end of 2002 and therefore 8 indices were not calculated.

7.4 Warsaw Stock Exchange

7.4.1 History

The first stock exchange in Poland opened in Warsaw on 1817 as the Mercantile Exchange. In the 19^{th} century, the exchange traded primarily bills of exchange and bonds. Equity trading developed on a larger scale in the second half of the century and continued until 1930s. After the break in the exchange's trading activity, caused by World War II, the operation was completely stopped by the subsequent changes in economic system. However, in 1989, along with political changes, the new non-communist government began creating a capital markets structure. The new legal framework, the Act on Public Trading in Securities and Trust Funds was adopted in March 1991, and Warsaw Stock Exchange joint-stock company was established by the State Treasury in April 1991.

The recent market development in the forms of market volume and capitalization together with the amounts of listed shares is presented in the table below.

Table 5 The development of Warsaw Stock Exchange since the year 1995
The market capitalization and turnover figures are in million PLN.

	2002	2001	2000	1999	1998	1997	1996	1995
Amount of Shares	216	230	225	221	198	143	83	65
Market Capitalization	110 565	103 370	130 085	123 411	72 442	43 766	24 000	11 271
Market Turnover	63 662	80 443	169 096	88 974	62 338	52 342	29 895	13 671

Since 1995 the amount of shares, market volume and capitalization were growing heavily until the year 2000. After this market turnover has decreased aggressively to its 1998 level while the amount of shares and market capitalization have decreased more moderately.

7.4.2 Current Operation

The opening hours of Warsaw Stock Exchanges are 8:30-16:30. The continuous equity trading hours are 10:00-16:00. Exchange day's schedule is described in appendix C.

In the end of 2002 there were 216 shares listed in the exchange. 135 of these were listed on the *Main market*, 56 on the *Parallel market* and 25 on the *Free market*.

Main market is the part of the exchange market that encompasses the securities with the highest liquidity. Additionally, issuers on the main market generally have more capital and longer histories.

Parallel market is the part of the exchange market that encompasses securities with lower liquidity. Additionally, issuers on the Parallel market generally have less capital and shorter histories than the companies on the Main market.

Free market is the part of the exchange market where traded shares are admitted for public trading, but do not meet requirements for listing on the Main or Parallel markets.

As it can be seen in the table 2, presented in the chapter 7.1.2, also WSE is quite concentrated. There are basically 5-11 liquid shares as the rest of the common stocks are traded with considerably lower volumes.

There are 11 indices reported in WSE: WIG, WIG20, MIDWIG, TechWIG, WIRR, NIF and 5 sector indices:

- The major WSE index is WIG that takes into account price changes of all the companies listed on the Main market, excluding National Investment Funds. WIG is weighted by each company's market value while a single company's share in the index cannot exceed 10%. Similarly, an individual sector's influence on WIG is limited to 30%. As WIG is an index analyzed also in this research, it will be described in more detail later in the chapter 7.5.2.
- WIG20 is calculated based on a portfolio comprised of shares of the 20 largest and most traded companies on the Main market. When selecting companies for the index, two criteria are taken into account. Those are turnover value, that is weighted with a factor 0.6, and market value, weighted by 0.4. Additionally, no more than five companies from a sector can participate the index.
- MIDWIG is calculated based on share values of not more than 40 companies on the Main, Parallel and Free markets, excluding the companies participating in WIG20 index. The composition of MIDWIG portfolio is based on the ranking, in which all companies meeting the minimum liquidity and free float criteria, are taken into account.
- TechWIG covers all companies qualified for SiTech[23]. A particular company's share in the index results from a ranking, while a company's position is determined by its relative share in SiTech turnover (weight 0.6) and capitalisation (weight 0.4) for the last six months. Simultaneously, the share of a company in the index is limited to 15%.
- WIRR i.e. Warsaw Parallel Market Index is weighted with market values of individual companies in the Parallel market. A single company's share in WIRR cannot exceed 10%. Similarly, individual sector's influence on WIRR is limited to 30%.
- NIF i.e. National Investment Funds index corresponds to the market value of shares in the National Investment Funds, received upon conversion of one NIF certificate.
- The sector indices comprise portions of the WIG index portfolio, selected based on sector criteria. The indices are WIG-banking, WIG-construction, WIG-IT, WIG-food and WIG-telecom.

[23] SiTech is a segment for companies operating in areas related to IT and telecommunication.

7.5 The Data Included in the Research

7.5.1 Equities

The equity data consists of trading information of thirteen shares traded in Budapest Stock Exchange (BSE), Prague Stock Exchange (PSE) and Warsaw Stock Exchange (WSE). The market selection was explained above and the share selection will be described now in more detail.

Basically, the objective in the share selection has been to choose shares that present at least 50% of the total market capitalization or annual trading volume taking into account sectoral classification of the shares. In other words, the selected shares should represent different business areas in each market. Additionally, to be able to have longer research periods, some high volume and capitalization companies, that have been listed only recently, have been excluded

Due to high concentration and small quantity of liquid shares in BSE, the selected four shares represent 90% of the total volume and 77% of the total market capitalization in BSE. Similarly, in PSE the selected four shares represent 83% of the total volume and 49% of the total market capitalization. Due to the lower concentration, more shares had to be selected from WSE. To be able to have 50% of the total volume or market capitalization and still to have early listed shares from different business areas, five shares were selected from WSE.

The data consists of closing prices that have been historically adjusted for dividends, splits and issues. In addition to its best availability, close price is chosen as it has been stated to represent the most common data applied in technical analysis. The data is collected from Datastream database.

The chosen shares, the used abbreviations, listing dates, markets and business areas together with the aforementioned sums of market volumes and capitalizations are listed below.

Table 6 The shares included in the research
The shares are listed together with their abbreviations, listing dates, markets, business areas and their share of the total market volume and capitalization in each market. The abbreviation column indicates the name each shares is called with later in this study.

Exchange	Company	Abbreviation	Listed	Market	Business	% of cap.	% of vol.
Budapest	Matáv Rt.	Matav	14/11/1997	-	Telecommunications	77%	90%
	MOL Rt.	Mol	28/11/1995	-	Oil, gas hydrocarbons		
	OTP Bank Rt.	Otp	10/08/1995	-	Finance and banking		
	Richter Gedeon Rt.	Richter	9/11/1994	-	Pharmaceuticals		
Prague	CESKÝ TELECOM a.s.	Cesky	14/3/1995	Main	Telecommunications	49%	83%
	CEZ a.s.	Cez	2/11/1993	Main	Power generation		
	Komercní banka a.s.	Komercni	21/3/1994	Main	Finance and banking		
	Philip Morris CR a.s.	Philip	9/11/1993	Free	Beverages & Tobacco		
Warsaw	Telekomunikacja Polska SA	Tpsa	18/11/1998	Main	Telecommunications	34%	50%
	Elektrim SA	Elektrim	26/3/1992	Main	Telecom. & power		
	KGHM Polska Mied' SA	Kghm	18/7/1999	Main	Metal		
	Bank Polska Kasa Opieki SA	Pekao	30/6/1998	Main	Banking		
	Prokom Software SA	Prokom	20/4/1998	Main	Information technology		

7.5.2 Indices

In addition to the shares, the major indices and their close values, reflecting the average profit gained in the market, are followed. The data is again collected from Datastream database. Below is a description of each index. Additionally, appendix D includes more detailed descriptions of all index bases in the end of 2002.

1. BUX: In BSE the major index is Budapest Stock Index (BUX). The index was published on January 2nd 1991. A maximum of 25 equities may be included in the index basket but e.g. in the end of 2002, the BUX basket comprised 14 stock series. The weight of an individual equity varied from OTP's 26.33% to Synergon's 0.35%. Although the weight of an equity in the index is fundamentally determined by the size i.e. capitalization of the issuing company, a relatively simple algorithm has been used to reduce the ratio of papers with extreme weights. The basket is reviewed twice a year.

2. PX 50: In PSE historically the oldest and most famous one is the official index PX 50 introduced on April 5th 1994. A standard method of calculation has been chosen for the index in accordance with the IFC methodology recommended for the creation of indices in emerging markets. The number of issues in the base can vary, but it must not exceed 50. Share of a constituent in the total market capitalization of the base is limited to 20%. Also equity sectoral classification has been taken into account. Investment fund issues are not included. In the end of 2002, PX 50 index base

consisted of 29 most attractive domestic stocks traded in the exchange. The weights varied from Komercní Banka's 21.60% to Ceská Zbrojovka's 0.07%. The basket is updated twice a year.

3. WIG: In WSE the index followed is the major WIG index that was published on April 16th 1991. The index is weighted with market values while WIG total market value should constitute 99% of the total Main market capitalisation. However, an individual company's participation is limited to 10% and an individual sector's participation is limited to 30% of the WIG portfolio. Again, the investment funds are excluded. In the end of 2002 the index included 77 companies. Each equity's weight varied from Pekao's 10.23% to BCZ's minimal weight that was less than 0.00%.

7.5.3 Portfolios

The selected equities and indices have been used to construct 5 portfolios. Three of these are country-specific Hungary (Hu), Czech (Cz) and Poland (Pl) portfolios including the shares chosen from each market. All the selected shares have been used to construct also a total share (Shr) portfolio while the fifth portfolio includes all the selected indices (Ind). The constituents are weighted equally in all the portfolios.

As there is no adjustment, Poland with five shares has a bit higher weight in the total start portfolio. Although this could be corrected by weighting the countries accordingly, all thirteen shares included in the research are still considered to represent different price developments in East European markets and therefore no adjustment has been used.

7.5.4 Periods

The trading performance has been evaluated on 1-4 different periods. The period lengths of *equities* have been selected with following rules:

- Period 1: The share that has been listed for the shortest period of time sets the start date for monitoring the performance. During this period all the time series included in the research are complete and comparable.
- Period 2: In each market, the share that has been listed for the shortest period of time sets now the start date for monitoring the performance. During this period all the share data from one market are complete and comparable.
- Period 3: The start date is defined by the issuing date of each equity. The time series are not comparable, but evaluated as they describe the overall behavior of each time series.

The period lengths of *indices* have been defined by the following rules:

- Period 1 and 2: The start dates follow the equities and therefore are the same as on the periods 1 and 2 of equities.
- Period 3: The start date is defined by the issue date of the index that has been issued most recently. During this period all the index data are complete and comparable.
- Period 4: The start date is defined by the publishing date of each index.

The period lengths of *portfolios* have been defined by the following rules:

- Period 1 and 2: The share that has been listed for the shortest period of time sets again the start date for monitoring the portfolio performance, because all the time series are complete only on these research periods. Therefore, the start dates are the same as on the periods 1 and 2 of equities.
- Period 3: The start date is defined by the issue date of the index that has been issued most recently. Therefore, the start date is the same as on the period 3 of indices.

Consequently, in period 1 all the equities, indices and portfolios are comparable and in period 2 only the investments in a single market can be compared. Period 3 of equities describes the total time series behavior, while with indices it can still be used to compare the indices to each other. Period 4 describes only the complete index time series development.

As the trading rules need some historical data to calculate the signals, the actual research periods still need some considerations. A period can't start before the time series data, needed to calculate all the rules, has been gathered. As the indicators requiring most historical data are the VMA rules comparing 1-day and 2-day short moving averages to 200-day long moving average, the start date of trading has to be postponed with 200 days. To be able to compare different rules during the same period, also other rules have to be postponed similarly. For example, the most recently listed equity Tpsa was listed on November 19th 1998. After postponing the start with 200 trading days, the period 1 can now start only on August 24th 1999.

All the period start and end dates are described in the following table. It should be noted that the end dates don't vary. The researched time series end date is always March 13th 2003.

Table 7 The different applied research periods together with their start and end dates

Market	Primary investment	Start date				End date
		Period 1	Period 2	Period 3	Period 4	
Hungary	Matav	24/8/1999	20/8/1998	20/8/1998	-	13/3/2003
	Mol	24/8/1999	20/8/1998	2/9/1996	-	13/3/2003
	Otp	24/8/1999	20/8/1998	15/5/1996	-	13/3/2003
	Richter	24/8/1999	20/8/1998	15/8/1995	-	13/3/2003
	Hu Portfolio	24/8/1999	20/8/1998	-	-	13/3/2003
	Bux	24/8/1999	20/8/1998	9/1/1995	8/10/1991	13/3/2003
Czech	Cesky	24/8/1999	18/12/1995	18/12/1995	-	13/3/2003
	Cez	24/8/1999	18/12/1995	8/8/1994	-	13/3/2003
	Komercni	24/8/1999	18/12/1995	23/12/1994	-	13/3/2003
	Philip	24/8/1999	18/12/1995	15/8/1994	-	13/3/2003
	Cz Portfolio	24/8/1999	18/12/1995	-	-	13/3/2003
	PX 50	24/8/1999	18/12/1995	9/1/1995	9/1/1995	13/3/2003
Poland	Tpsa	24/8/1999	24/8/1999	24/8/1999	-	13/3/2003
	Elektrim	24/8/1999	24/8/1999	30/12/1992	-	13/3/2003
	Kghm	24/8/1999	24/8/1999	23/4/1998	-	13/3/2003
	Pekao	24/8/1999	24/8/1999	5/4/1999	-	13/3/2003
	Prokom	24/8/1999	24/8/1999	22/1/1999	-	13/3/2003
	Pl Portfolio	24/8/1999	24/8/1999	-	-	13/3/2003
	Wig	24/8/1999	24/8/1999	9/1/1995	20/1/1992	13/3/2003
All	Shr Portfolio	24/8/1999	-	-	-	13/3/2003
	Ind Portfolio	24/8/1999	24/8/1999	9/1/1995	-	13/3/2003

It should be noticed that when different periods have the same start date, the test starting from this date is implemented only once. For example, the most recently listed Tpsa time series data has been tested only once although there are two research periods mentioned.

8 RESULTS

The research was carried out with the methodology described above in chapter 6. This chapter describes the results when these methods have been applied to the selected time series data presented in chapter 7. However, first the general properties of the original time series are described.

8.1 Original Time Series Behavior

The following picture describes the behavior of BUX index and selected BSE share prices from the issuing days until the end of the research period.

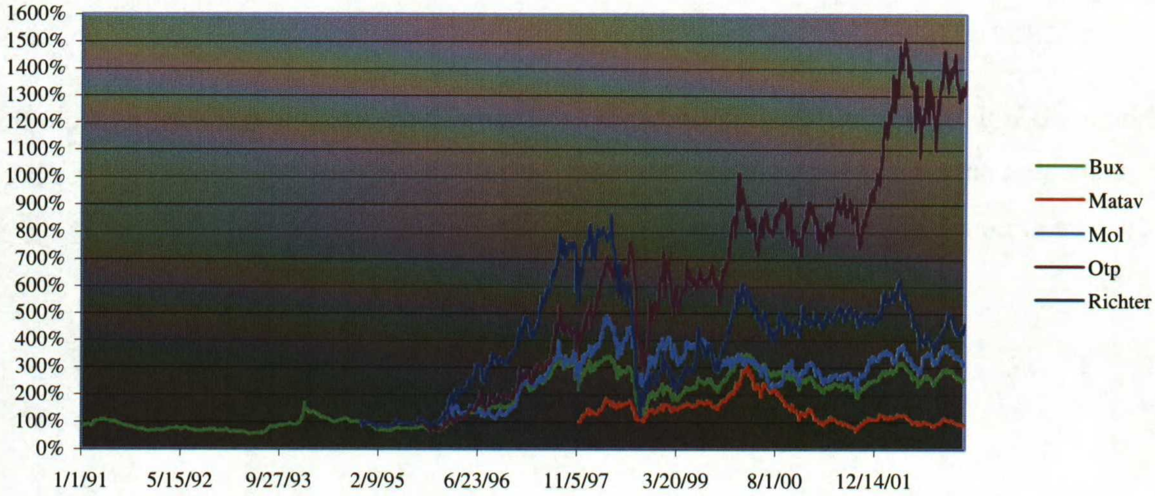

Figure 7 The development of BSE data included in the research
The data consists of BUX index and four shares included in the research. Each issuing level is indicated as 100%.

It can be noticed that almost all the values have increased considerably since the issuings of the indices and shares. Only Matav's end value almost equals its issue value. This might have provided a fertile basis for a profitable buy & hold strategy. Especially, if the money was invested in Otp on the day it was listed, the investment nominal value would have been 12 times higher in the end of the research period. Also an investor employing technical analysis may have profited from the rising trends, but the actual technical analysis profits exceeding buy & hold profits can be seen only in the following chapter.

On shorter periods, for example on period 1 starting from August 24th 1999, the profitability of different strategies is not that clear and cannot be evaluated only by observing the graph. Therefore, these will be discussed more precisely starting from chapter 8.3.

The following picture describes the behavior of PX 50 index and selected PSE share prices from the issuing days until the end of the research period.

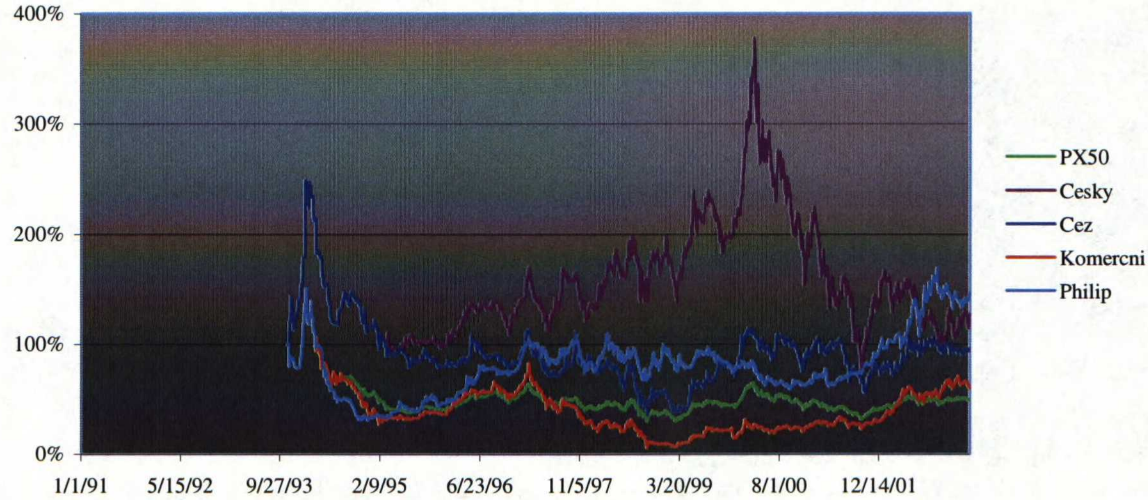

Figure 8 The development of PSE data included in the research
The data consists of PX 50 index and four shares included in the research. Each issuing level is indicated as 100%.

It can be noticed that the end values of all the time series are reasonably close to their start values. Therefore, to speculate the possibilities of technical trading rules, in order to provide abnormal profits, the rules have to be sensitive enough to exploit the smaller fluctuations. This concerns especially Cesky. Although its nominal value has occasionally been almost 400% of the start value, the sharp downturns in the stock price would have required a sensitive indicator that advices to sell early enough.

On the other hand, abnormal profits can also be interpreted as smaller losses when active trading results are related to the buy & hold strategy results. From this point of view, in this research an optimal strategy should also have the feature to warn the investor from downtrend by giving an early sell signal. Again, a sensitive strategy would signal the investor as early as possible.

The following picture describes the behavior of WIG index and selected WSE share prices from the listing days until the end of the research period.

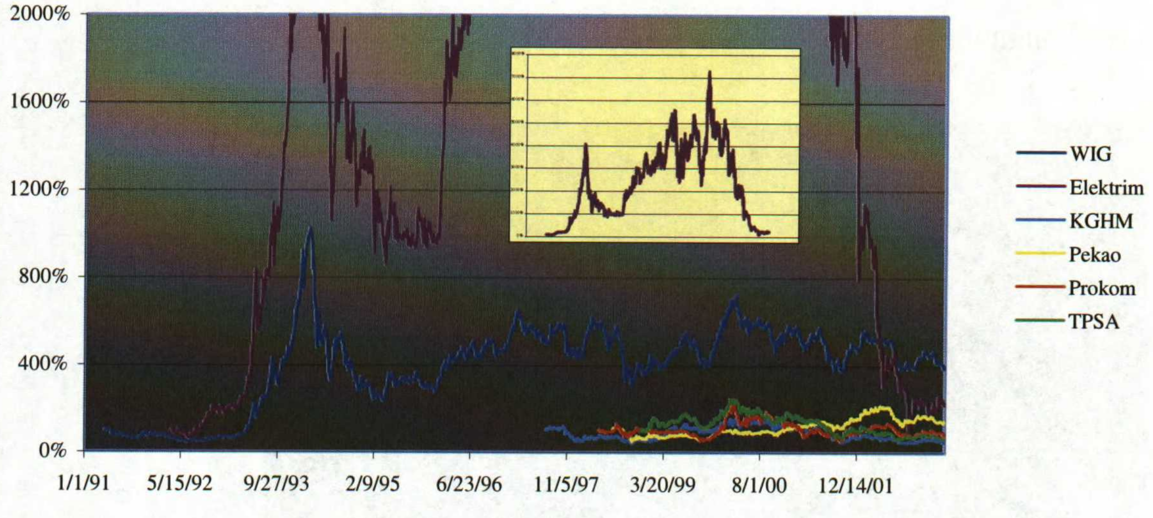

Figure 9 The development of WSE data included in the research
The data consists of WIG index and five shares included in the research. Each issuing level is indicated as 100%. The small figure indicates the Elektrim share price overall development.

It can be noticed that all time series, instead of the WIG index, end values are reasonably close to their start values. While four series fluctuate quite moderately, Elektrim and WIG index have been varying heavily. The similar movement is also due to the considerably high market capitalization giving Elektrim a remarkable impact on WIG. Indicated by the small figure, the Elektrim nominal value has been occasionally more than 75 times higher when related to its issuing price. Consequently, Elektrim has provided an investor applying active trading methods a possibility to gain considerable profits.

8.2 Statistical Testing

The actual research was started by surveying original time series stationarity with Dickey-Fuller tests. The following table shows the test results separately for each of the shares and indices since the issuing date until the end of the research period i.e. on periods 3 and 4. The test results are *t*-statistics that indicate possible stationarity when lower than the critical value -2.57 selected in the chapter 6.3.1.3.

Table 8 The results of Dickey-Fuller tests
The figures indicate the t-statistics and their possible indication of stationarity.

Market	Share/Index	t-statistic	Indication of stationarity
Hungary	Matav	-1.41985	-
	Mol	-2.62373	Yes
	Otp	-0.75892	-
	Richter	-1.85648	-
	Bux	-1.195	-
Czech	Cesky	-1.9283	-
	Cez	-2.29444	-
	Komercni	-3.15491	Yes
	Philip	-0.90176	-
	PX 50	-6.41063	Yes
Poland	Tpsa	-1.34861	-
	Elektrim	-1.76641	-
	Kghm	-1.65303	-
	Pekao	-1.19655	-
	Prokom	-2.53982	-
	Wig	-1.95425	-

It can be noticed that the null hypothesis was rejected in only three cases i.e. according to the *t*-statistics only three of the researched time series appeared stationary.

Autocorrelation has been researched with 1- to 25-day lags. When the research was first implemented with the original price data the autocorrelation tests showed almost 100% autocorrelation indicating the need for further investigating with processed data. At this point the stationarity test results have to be taken into account. In the case of the three stationary time series, the research will concentrate on residuals while the non-stationary series will be differenced.

The following table shows all the autocorrelations of either residuals or first-order differenced data depending on the original time series stationarity. Box-Pierce Q value in the second last column indicates the possible significances of the explored autocorrelations.

Table 9 Autocorrelations of researched time series data

The figures indicate the autocorrelations with 1- to 25-day lags. Additionally the table indicates the Box-Pierce Q values reflecting the autocorrelation significances of all time series researched in the study. Additionally, the last column indicates, whether the research was made with residuals (R) or first-order differenced (D) data.

	Share/ Index	Lag 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	Q	D/R
Hungary	Matav	0.050	0.010	-0.021	-0.030	0.016	-0.072	0.004	0.019	0.078	0.000	0.008	0.036	0.025	0.057	-0.066	0.006	0.013	0.068	0.017	0.042	0.035	-0.025	0.027	0.035	0.025	51.07	D
	Mol	0.044	0.034	-0.055	-0.011	-0.019	-0.052	0.001	-0.008	0.055	0.043	0.007	0.050	0.030	0.027	0.013	-0.021	-0.024	-0.006	0.015	-0.004	0.011	-0.006	0.000	-0.027	0.058	45.93	R
	Otp	0.006	0.003	-0.089	0.004	-0.019	-0.054	0.002	0.004	-0.008	-0.019	0.032	0.042	0.029	0.005	0.007	-0.023	-0.024	0.052	0.038	-0.008	-0.016	0.011	-0.006	0.017	0.018	43.09	D
	Richter	0.053	0.036	-0.051	-0.027	-0.023	-0.025	-0.050	0.020	0.012	0.048	0.065	0.042	0.073	-0.014	0.041	0.008	-0.014	0.017	0.030	0.004	-0.029	0.008	0.013	-0.012	0.001	64.91	D
	Bux	0.029	0.041	-0.054	0.000	0.001	-0.055	-0.021	0.031	0.036	0.052	0.041	0.072	0.048	0.017	0.006	-0.008	-0.003	-0.004	0.029	0.000	0.011	-0.009	0.034	-0.009	0.031	83.49	D
Czech	Cesky	0.046	0.011	0.003	-0.001	-0.019	-0.045	-0.035	0.013	-0.003	0.024	0.035	0.021	0.040	-0.013	0.124	0.041	-0.035	-0.032	-0.037	-0.026	-0.056	-0.036	0.009	0.043	0.038	81.86	D
	Cez	0.014	-0.007	0.011	0.048	-0.048	-0.016	0.009	0.091	-0.060	0.017	0.036	0.005	-0.008	0.102	0.007	-0.005	-0.008	0.025	0.023	-0.016	-0.039	0.069	0.000	0.014	0.030	93.31	D
	Komercni	0.106	-0.023	-0.016	0.023	-0.015	-0.078	0.016	-0.018	0.049	0.059	0.020	-0.020	0.017	0.009	-0.026	-0.009	-0.053	-0.015	0.027	0.028	0.007	0.012	0.040	0.032	0.013	81.53	R
	Philip	0.024	0.043	0.030	-0.008	0.018	-0.042	-0.034	0.074	0.029	-0.006	-0.009	0.016	0.023	0.014	-0.034	0.026	0.032	0.003	-0.056	-0.015	0.037	-0.025	-0.012	-0.019	-0.002	55.53	D
	PX 50	0.118	0.090	0.051	0.042	0.003	-0.029	-0.014	0.013	0.028	0.026	0.029	0.037	0.043	0.014	0.073	0.010	0.007	0.023	-0.013	0.013	-0.025	0.015	0.034	0.042	0.034	103.98	R
Poland	Tpsa	-0.014	-0.019	-0.031	0.003	-0.001	-0.046	-0.012	0.038	0.043	0.002	-0.021	-0.056	0.119	0.048	0.047	-0.015	-0.059	-0.017	-0.011	-0.074	-0.027	0.043	0.053	0.019	0.003	50.36	D
	Elektrim	0.022	0.063	-0.006	0.016	-0.061	-0.056	-0.030	0.025	-0.018	0.047	0.031	0.032	0.046	-0.038	0.043	0.011	-0.018	-0.017	-0.024	-0.019	-0.013	-0.005	0.041	-0.003	0.005	76.20	D
	Kghm	-0.008	-0.021	-0.023	-0.001	-0.036	0.029	-0.054	-0.014	0.018	0.029	-0.018	-0.011	0.064	-0.023	0.058	0.011	-0.021	-0.074	-0.026	-0.016	0.013	0.002	0.031	-0.054	0.060	44.99	D
	Pekao	-0.038	0.058	-0.055	-0.009	-0.014	-0.038	0.033	0.006	0.017	0.030	-0.049	0.043	0.006	0.012	0.048	-0.034	-0.007	0.008	0.018	0.021	-0.024	-0.022	0.048	-0.010	0.050	32.66	D
	Prokom	-0.075	0.044	-0.021	0.053	-0.051	-0.091	-0.029	0.028	-0.038	0.017	0.138	-0.045	0.143	-0.053	0.090	-0.018	-0.006	-0.028	-0.035	0.015	-0.008	-0.075	0.021	0.072	-0.004	116.90	D
	Wig	0.147	0.069	-0.015	-0.001	-0.030	0.000	0.050	0.062	0.030	0.092	0.018	0.006	0.057	0.020	0.003	0.010	0.004	0.034	-0.036	0.035	-0.018	0.011	-0.011	0.003	-0.026	162.44	D

When using the confidence level 95% and degree of freedom 24, Box-Pierce gives critical autocorrelation level 36.42. It can be now noticed that even after using the residuals or first-order differenced time series, almost all Q values exceeded this critical level i.e. series included significant autocorrelation, which suggests that market prices don't follow random walk. Only Pekao did not appear to be significantly autocorrelated. These results were double-checked with other common confidence levels, but the critical values were still lower than those twelve Q values calculated for researched time series.

Like mentioned earlier, e.g. Harvey (1995b) suggested that the level of autocorrelation is directly associated to the size and the degree of concentration of the market. As the selected markets simultaneously appear as very concentrated and autocorrelated ones, this research supports the theory.

Especially, the index autocorrelation proved the markets to have also characteristics typical for an illiquid market. Further, to relate the achieved figures to other previous observations, the Lo & MacKinlay (1988) study is referred. They conclude that especially the smaller capitalization stocks do not seem to follow the random walk. However, in this study even the higher capitalization ones included significant autocorrelation. On the other hand, the earlier conclusion is supported by the fact that only share without significant autocorrelation, Pekao, is a high capitalization stock representing 14% of the WSE total capitalization.

The statistical approach is completed with runs tests. As mentioned in chapter 6.3.3.3, for runs tests the data is divided in price changes below and above the median. As the price change series already act as first-order differenced price data series, for non-stationary series no further processing is required. However, in the case of the stationary time series, the research will again concentrate on residuals produced in analyzing the regression between price change and delayed series. The following table 10 represents the results i.e. Z values of the runs tests.

Table 10 The results of the runs tests
The figures indicate the calculated Z values of either first-order differenced time series or residuals.

Market	Share/Index	Z	Runs test employed for
Hungary	Matav	-1.180	Derivative
	Mol	-2.752	Residuals
	Otp	-1.430	Derivative
	Richter	-2.873	Derivative
	Bux	-4.106	Derivative
Czech	Cesky	-1.375	Derivative
	Cez	-0.541	Derivative
	Komercni	-3.988	Residuals
	Philip	-2.289	Derivative
	PX 50	-5.780	Residuals
Poland	Tpsa	0.379	Derivative
	Elektrim	-2.555	Derivative
	Kghm	0.385	Derivative
	Pekao	0.054	Derivative
	Prokom	-0.439	Derivative
	Wig	-5.289	Derivative

In eight out of sixteen cases the Z value is not between –1.96 and +1.96, which indicates that the runs above and below the median price change did not occur by chance alone and that the price changes are probably not normally distributed. However, like concluded by Urrutia (1995), the results don't suggest that equity markets will show up completely weak form efficient. In order to define the market efficiency, the possibilities to make abnormal profits still have to be evaluated.

Now the results of parametric and non-parametric tests can be compared. It can be noticed that all the results provided by runs tests were also supported by the autocorrelation tests.

8.3 Buy & Hold Strategy

Before concentrating on the trading success, the buy & hold strategy profitability, acting as a benchmark, is first reported. The following table 11 represents separately the relative values (in percentages when compared to the initial investment) and annualized Sharpe measures of all investments on March 13th 2003.

Table 11 Buy & hold strategy profitability
Investment profitability i.e. the relative values and annualized Sharpe measures of all the separate investments after buy & hold strategy has been applied on each of the research periods.

Market	Primary investment	Nominal profit				Sharpe ratio			
		Period 1	Period 2	Period 3	Period 4	Period 1	Period 2	Period 3	Period 4
Hungary	Matav	-47.14%	-39.62%	-39.62%		-0.36158	-0.13606	-0.13606	
	Mol	-16.86%	-14.99%	169.42%		-0.05068	0.05198	0.63266	
	Otp	121.67%	127.80%	945.88%		0.90604	0.69526	1.11993	
	Richter	29.34%	21.93%	441.95%		0.39128	0.36297	0.79205	
	Portfolio	21.75%	23.78%			0.26694	0.32655		
	Bux	1.64%	0.61%	186.57%	234.39%	0.08881	0.13778	0.60372	0.52714
Czech	Cesky	-43.26%	30.49%	30.49%		-0.20647	0.28687	0.28687	
	Cez	48.23%	21.33%	-30.35%		0.52249	0.25639	0.03073	
	Komercni	160.35%	83.39%	79.42%		0.99953	0.45021	0.41318	
	Philip	116.01%	476.14%	488.86%		0.93637	1.01445	0.88428	
	Portfolio	70.33%	152.84%			0.28687	-0.20647		
	PX 50	4.77%	23.35%	-11.38%	-11.38%	0.11357	0.19319	-0.04851	-0.04851
Poland	Tpsa	-58.19%	-58.19%	-58.19%		-0.37884	-0.37884	-0.37884	
	Elektrim	-94.79%	25.00%	25.00%		-0.68677	0.44092	0.44092	
	Kghm	-50.95%	-27.37%	-27.37%		-0.32601	0.09044	0.09044	
	Pekao	105.70%	112.18%	112.18%		0.82178	0.78658	0.78658	
	Prokom	4.46%	-9.83%	-9.83%		0.32772	0.22970	0.22970	
	Portfolio	-18.75%	-18.75%			-0.37884	-0.37884		
	Wig	-20.43%	-20.43%	30.89%	431.05%	-0.18606	-0.18606	0.24173	0.63732
All	Shr Portfolio	24.44%				-0.21325			
	Ind Portfolio	-4.67%	-4.67%	18.28%		-0.00459	-0.00459	0.38653	

Buy & hold profits varied from –94.79% to 945.88%, which could have been also roughly estimated with the figures 7, 8 and 9. Although the Sharpe measures do not always follow the levels and superiority of buy & hold profits, the lowest and highest Sharpe values are represented by the same shares and periods. There seems to be no common characteristics in buy & hold profits or Sharpe measures of shares and indices. However, it can be noticed that sometimes the indices and portfolios provided similar results especially when the performance was measured with nominal profits. This is actually natural, as the contents of involved indices and established portfolios are quite similar.

8.4 Trading

Finally, this chapter runs through the trading results. First the research data is summarized and related glossary is introduced:

- There are 21 different investment opportunities called as *primary investments*. These include 13 shares, 3 indices and 5 portfolios.
- 13 *shares* include 4 different shares from both BSE and PSE and 5 shares from WSE.
- 3 *indices* include the major index from each market.
- 3 *country-specific portfolios* are established with selected shares from each of the respective markets, while the *total equity portfolio* consists of these all. The fifth i.e. the *index portfolio* includes all three indices.

Due to the high amount of trading simulations, the results have been listed according to different variables defining the exact methodology. Simultaneously, this clarifies the evaluation of the effects of these methodology variations. As a summary, the different variables include

- 111 different trading rules containing 15 MA, 6 RSI and 90 combination rules. The varying MA rule parameters include different long and short moving averages and different trading bands. The RSI rule variations mean different neutralization levels and calculation periods. The number of different combination rules depends just on the amount of combinations of different MA and RSI rules.
- 8 different one-way trading costs. These were 0%, 0.5%, 1.0%, 1.5%, 2.0%, 2.5%, 3.0% and 3.5%.
- 1-4 different periods. The equities were tested on 1-3, portfolios on 1-2 and indices on 3-4 different periods.
- 2-3 different secondary investments. When the applied trading rule gives a sell signal the current value of the primary investment is invested in a so-called secondary investment. In more detail, the money is invested now with a fixed annual interest rate of 0% or 2% or invested in the local index. Naturally, after an index sell signal, only the two fixed interest rates are appropriate secondary investments.
- 2 different performance indicators including monetary profit and Sharpe measure.

The 111 different trading rules together with 3 different secondary investments mean 333 different strategies to be applied for each share and portfolio on 1-3 different time periods. 2 different secondary investment possibilities total 222 different strategies to be applied for each index series on 3-4 different time periods. In sum, all these different variations mean total of 14 985 different trading simulations implemented with each of the 8 different trading cost levels. The results include both profit figures and Sharpe measures.

The tables below go over the main points of trading results and simultaneously show the effects of abovementioned methodology variations. Because the main interest lies in market efficiency evaluation, the tables indicate mainly the amounts of successful trading simulations revealed by the quantities of abnormal profits and abnormal Sharpe ratios[24]. Some complementary information is presented in the chapter 8.5.

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[24] Active trading produces abnormal profit when a simulation applying a trading rule brings a profit exceeding the respective buy & hold profit. Respectively, the Sharpe measures exceeding the ones gained with buy & hold strategy are considered as abnormal Sharpes.

8.4.1 Different Trading Costs

The major relevance of evaluating the effects of trading costs has been highlighted in the previous studies. However, the effects have been rarely demonstrated. This chapter discusses the general trading results and the effects of increasing trading costs summarized first in the table 12 below.

Table 12 Trading results classified by primary investments and trading cost levels
The table includes the numbers of abnormal profits and abnormal Sharpes gained with eight different trading cost levels. Additionally, the amounts of simulations implemented for each of the primary investments are presented. The different trading costs levels were 0, 0.5%, 1.0%, 1.5%, 2.0%, 2.5%, 3.0% and 3.5%. The columns indicate the highest level of trading costs still providing abnormal profits. For example 2% of the Matav simulations have provided abnormal profits only with 0% trading costs. The column 3.5% includes the number of trading simulations gaining abnormal profits after introducing trading costs of 3.5%. Consequently, abnormal figures could still be gained after initiating even higher trading costs. The figures include all rule variations, secondary investments and periods. Due to rounding, some sum figures appear different from the values calculated by totaling the figures in respective columns or rows.

	Primary investment	Qty. of simula-tions	Number of simulations providing abnormal profits									Percentage of simulations providing abnormal profits									Abnormal Sharpes	
			0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	Sum	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	Sum	Qty	%
Hungary	Matav	666	16	64	114	92	83	50	47	184	650	2	10	17	14	12	8	7	28	98	476	71
	Mol	999	178	91	24	11	16	12	5	8	345	18	9	2	1	2	1	1	1	35	257	26
	Otp	999	1	1	0	0	0	0	0	2	4	0	0	0	0	0	0	0	0	0	12	1
	Richter	999	132	30	15	12	12	7	3	8	219	13	3	2	1	1	1	0	1	22	387	39
	Hu Portfolio	666	73	3	1	1	2	0	0	3	83	11	0	0	0	0	0	0	0	12	78	12
	Bux	888	210	133	51	29	22	29	6	34	514	24	15	6	3	2	3	1	4	58	489	55
Czech	Cesky	666	35	80	76	63	27	14	11	40	346	5	12	11	9	4	2	2	6	52	246	37
	Cez	999	246	93	52	22	12	5	4	8	442	25	9	5	2	1	1	0	1	44	287	29
	Komercni	999	37	22	34	40	24	17	7	15	196	4	2	3	4	2	2	1	2	20	257	26
	Philip	999	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	30	3
	Cz Portfolio	666	12	1	0	0	0	0	0	0	13	2	0	0	0	0	0	0	0	2	439	66
	PX 50	666	123	61	28	8	5	0	0	12	237	18	9	4	1	1	0	0	2	36	276	41
Poland	Tpsa	333	21	31	49	50	50	37	20	67	325	6	9	15	15	15	11	6	20	98	185	56
	Elektrim	666	48	20	29	16	16	23	11	370	533	7	3	4	2	2	3	2	56	80	398	60
	Kghm	666	94	97	69	52	35	21	22	150	540	14	15	10	8	5	3	3	23	81	226	34
	Pekao	666	10	0	0	0	1	0	1	2	14	2	0	0	0	0	0	0	0	2	91	14
	Prokom	666	93	117	95	53	24	13	8	20	423	14	18	14	8	4	2	1	3	64	307	46
	Pl Portfolio	333	90	87	41	12	7	5	1	18	261	27	26	12	4	2	2	0	5	78	260	78
	Wig	666	130	97	138	52	21	16	13	6	473	20	15	21	8	3	2	2	1	71	257	39
All	Shr Portfolio	333	10	0	0	0	0	0	0	0	10	3	0	0	0	0	0	0	0	3	251	75
	Ind Portfolio	444	151	63	11	4	2	4	3	3	241	34	14	2	1	0	1	1	1	54	235	53
	Sum	14985	1711	1091	827	517	359	253	162	950	5870	11	7	6	3	2	2	1	6	39	5444	36

First the general trading results are reviewed. It can be noticed that in 39% of all the simulations, active trading brought abnormal profits. However, the success of technical analysis varied considerably between different shares, indices and portfolios as the lowest amount of abnormal profits was 2% and the highest 98%.

When the market efficiency on each of the markets is evaluated, the main interest lies in the portfolios and indices reflecting the average market characteristics. Also the results of established country-specific portfolios varied heavily from 2% of Czech to 78% of Poland. Simultaneously, the profits brought by selected major indices varied more moderately as active trading with PX 50 index brought abnormal profits in least i.e. 36% of the cases while Wig brought abnormal profits in most i.e. 71% of the cases.

The total share and index portfolios provide additional information on the total efficiency of these three markets. If the money was divided equally in all the shares, trading profited the investor only in 3% of the cases. With index portfolio the abnormal profits were gained in 54% of the cases.

Based on these results, at least Polish market might be interpreted as an inefficient one. However, no conclusions should be drawn before the trading costs are introduced. The great amount of trades increased the importance of trading costs, which can be noticed also from the table. For example, the sum row indicates that 11% of the simulations were profitable only with the 0% trading costs. Only in 6% of the cases the trading brought abnormal profits with highest 3.5% trading costs.

Although already introduction of 0.5% trading costs affected the results remarkably, more relevant results are provided by figures reflecting the trading success after more realistic trading cost levels. As mentioned above in the chapter 7.1.1, it has been surveyed that average round-trip trading costs in emerging markets have been 1.80% while the highest 3.59% trading costs have been found in Czech markets. As the transaction costs reported in this study are one-way trading costs, by summing the figures in the columns 2.0-3.5, it can be seen that in reality active trading would have gained abnormal profits at least in 11% of the cases. But if the average trading costs are assumed to apply, the columns 1.0-3.5 indicate that 20% of the cases would have brought abnormal profits for active traders. However, again the success of technical analysis varied between different primary investments. Consequently, the results are now divided for shares, indices and portfolios:

- When 1.0% one-way trading costs were applied in share trading, the relative amounts of abnormal profits ranged between 0 and 86%. The shares providing abnormal profits in more than half of the cases were Matav, Tpsa, Elektrim and Kghm. With 2.0% one-way trading costs, the relative amounts of abnormal profits ranged between 0 and 63%. The only shares providing abnormal profits in more than half of the cases were Matav, Tpsa and Elektrim.
- The only country-specific portfolio providing abnormal profits, even after trading costs were involved, was the Polish one. With 1.0% one-way trading costs, the active trading with portfolio shares brought abnormal profits in 25% of the cases. When the costs rose to 2.0%, the relative amount of abnormal profits decreased to 9.0%.
- With indices the relative amounts of abnormal profits, when 1.0% and 2.0% trading costs were applied, were again below 50%. For Bux the figures were 19% and 10%, for PX 50 8% and 3% and for Wig 37% and 8%.

- The total share portfolio brought no abnormal profits after trading costs were introduced.
- The index portfolio brought abnormal profits only in 6% and 3% of these cases when the trading costs were 1.0% and 2.0%, respectively.

These results indicate that from all primary investments only 3-4 of the selected shares may have been traded profitably. Also Poland portfolio and Wig index gained abnormal profits in more than 50% of the cases even after lowest applied trading costs, but these figures decreased considerably after 1.0% trading costs, approximately equaling average emerging market round-trip costs, were applied. Consequently, none of the markets can be interpreted as inefficient ones.

The Sharpe ratios, on the other hand, favored the time series re-constructed with technical trading rules. However, stable secondary investments with fixed 0% and 2% interest rates can increase the ratios considerably. Therefore, the Sharpe ratio evaluation is more relevant later when the effects of different secondary investments have been taken into account.

When the trading results are compared to the results obtained with statistical tools, not too much correspondence can be found. The first observation supporting the connection between autocorrelation and market inefficiency was that Pekao, the only series with non-significant autocorrelation, provided almost no abnormal profits and the only profits disappeared when the trading costs were introduced. Simultaneously, the series with highest autocorrelations did produce above-average number of abnormal profits. However, the series providing abnormal profits in as many as 98% of the simulations, included autocorrelation just slightly above the significant level.

The general effect of increasing trading costs has now been introduced and the following tables concentrate on evaluating the effects of other variables. As the results gained without and with any trading costs differ drastically, the trading cost effects are not completely ignored. The results are still divided to the ones gained with and without trading costs. The columns labeled with >0 present the situation after lowest 0.5% trading costs have been employed.

8.4.2 Different Trading Rules

To be able to present the effects of trading rule variations and to compare the results of all 111 different trading rules they are first summarized in a single table below.

Table 13 The profitability of different trading rules
The different columns show the effects of three different trading bands. The first columns labeled with Band Stdev show the amounts of abnormal profits gained with band of one standard deviation, the second set of columns shows the amounts of abnormal profits gained with 1% band and the last ones show the amounts when no band has been used. As RSI rules were not tried with a band, all the RSI figures are presented in the Band 0% columns. The columns marked with 0 show the amounts of abnormal profits gained only without trading costs while >0 includes the profits gained with 0.5% trading costs. The figures are sum figures including all secondary investment and period variations for each of the primary investments. Both amounts and relative amounts of the cases producing abnormal profits are presented.

				Number of simulations providing abnormal profits												Percentage of simulations providing abnormal profits											
				Band Stdev			Band 1%			Band 0%			Sum			Band Stdev			Band 1%			Band 0%			Sum		
				0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum
MA			1:50	31	59	90	31	57	88	27	59	86	89	175	264	23	44	67	23	42	65	20	44	64	22	43	65
			1:150	22	40	62	20	41	61	27	35	62	69	116	185	16	30	46	15	30	45	20	26	46	17	29	46
			5:150	15	45	60	14	45	59	18	42	60	47	132	179	11	33	44	10	33	44	13	31	44	12	33	44
			1:200	18	47	65	19	44	63	18	45	63	55	136	191	13	35	48	14	33	47	13	33	47	14	34	47
			2:200	16	49	65	17	49	66	13	51	64	46	149	195	12	36	48	13	36	49	10	38	47	11	37	48
RSI	5d		30/70	-	-	-	-	-	-	52	8	60	52	8	60	-	-	-	-	-	-	39	6	44	39	6	44
			20/80	-	-	-	-	-	-	30	11	41	30	11	41	-	-	-	-	-	-	22	8	30	22	8	30
	14d		30/70	-	-	-	-	-	-	13	41	54	13	41	54	-	-	-	-	-	-	10	30	40	10	30	40
			20/80	-	-	-	-	-	-	9	32	41	9	32	41	-	-	-	-	-	-	7	24	30	7	24	30
	21d		30/70	-	-	-	-	-	-	11	51	62	11	51	62	-	-	-	-	-	-	8	38	46	8	38	46
			20/80	-	-	-	-	-	-	1	65	66	1	65	66	-	-	-	-	-	-	1	48	49	1	48	49
Combined	5d	30/70	1:50	33	36	69	36	30	66	40	26	66	109	92	201	24	27	51	27	22	49	30	19	49	27	23	50
			1:150	27	27	54	19	27	46	18	26	44	64	80	144	20	20	40	14	20	34	13	19	33	16	20	36
			5:150	26	30	56	23	25	48	22	21	43	71	76	147	19	22	41	17	19	36	16	16	32	18	19	36
			1:200	20	31	51	22	28	50	22	27	49	64	86	150	15	23	38	16	21	37	16	20	36	16	21	37
			2:200	24	31	55	18	31	49	17	29	46	59	91	150	18	23	41	13	23	36	13	21	34	15	22	37
		20/80	1:50	22	40	62	16	40	56	20	36	56	58	116	174	16	30	46	12	30	41	15	27	41	14	29	43
			1:150	17	30	47	8	32	40	10	29	39	35	91	126	13	22	35	6	24	30	7	21	29	9	22	31
			5:150	14	35	49	14	32	46	13	29	42	41	96	137	10	26	36	10	24	34	10	21	31	10	24	34
			1:200	7	36	43	8	31	39	9	29	38	24	96	120	5	27	32	6	23	29	7	21	28	6	24	30
			2:200	9	35	44	4	36	40	6	34	40	19	105	124	7	26	33	3	27	30	4	25	30	5	26	31
	14d	30/70	1:50	14	46	60	12	45	57	16	42	58	42	133	175	10	34	44	9	33	42	12	31	43	10	33	43
			1:150	14	29	43	8	28	36	11	24	35	33	81	114	10	21	32	6	21	27	8	18	26	8	20	28
			5:150	10	30	40	5	28	33	4	29	33	19	87	106	7	22	30	4	21	24	3	21	24	5	21	26
			1:200	14	29	43	9	27	36	9	27	36	32	83	115	10	21	32	7	20	27	7	20	27	8	20	28
			2:200	10	30	40	8	27	35	8	27	35	26	84	110	7	22	30	6	20	26	6	20	26	6	21	27
		20/80	1:50	25	36	61	23	39	62	22	32	54	70	107	177	19	27	45	17	29	46	16	24	40	17	26	44
			1:150	16	33	49	10	27	37	8	28	36	34	88	122	12	24	36	7	20	27	6	21	27	8	22	30
			5:150	4	42	46	11	30	41	5	32	37	20	104	124	3	31	34	8	22	30	4	24	27	5	26	31
			1:200	9	42	51	12	33	45	12	28	40	33	103	136	7	31	38	9	24	33	9	21	30	8	25	34
			2:200	8	40	48	7	39	46	12	32	44	27	111	138	6	30	36	5	29	34	9	24	33	7	27	34
	21d	30/70	1:50	24	43	67	25	44	69	31	38	69	80	125	205	18	32	50	19	33	51	23	28	51	20	31	51
			1:150	19	40	59	10	41	51	13	41	54	42	122	164	14	30	44	7	30	38	10	30	40	10	30	40
			5:150	13	36	49	10	35	45	11	35	46	34	106	140	10	27	36	7	26	33	8	26	34	8	26	35
			1:200	14	44	58	17	42	59	18	38	56	49	124	173	10	33	43	13	31	44	13	28	41	12	31	43
			2:200	10	44	54	16	44	60	14	42	56	40	130	170	7	33	40	12	33	44	10	31	41	10	32	42
		20/80	1:50	11	63	74	12	59	71	14	53	67	37	175	212	8	47	55	9	44	53	10	39	50	9	43	52
			1:150	14	46	60	10	46	56	12	40	52	36	132	168	10	34	44	7	34	41	9	30	39	9	33	41
			5:150	9	49	58	6	49	55	2	52	54	17	150	167	7	36	43	4	36	41	1	39	40	4	37	41
			1:200	12	46	58	12	45	57	17	40	57	41	131	172	9	34	43	9	33	42	13	30	42	10	32	42
			2:200	8	47	55	13	47	60	12	44	56	33	138	171	6	35	41	10	35	44	9	33	41	8	34	42
Sum				675	1594	2269	505	1323	1828	531	1242	1773	1711	4159	5870	12	29	41	11	28	39	11	26	38	11	28	39

When the different trading rule types are compared, the moving averages seem to be most profitable. The amounts of abnormal profits gained with MA rules ranged from 44% to 65% while the average was 50%. However, already the after lowest 0.5% trading costs the average was only 35%. RSIs gave figures between 30% and 49% while the average was 40%. Again after the 0.5% trading costs the average decreased to only 26%. Combinations provided profits least frequently. Depending on applied rules the percentages ranged now from 26 to 52. Before trading costs the average was 37%, but after lowest trading costs only 27%.

From different rule variations, most profitable was the MA (1,50,B) rule based on averages computed for 1 and 50 days, used together with the standard deviation band B. The method produced abnormal profits in 67% of the cases. However, after 0.5% trading costs were introduced, the method was profitable in only 44% of the cases.

When the trading bands are compared, it can be noticed that in nearly all the cases the band of one standard deviation profited the investor most frequently. Simultaneously, the superiority of bands 1% and 0% varied. Therefore, it can be concluded that the risk-adjustment through the use of standard deviation band, recommended also by Ratner & Leal (1999), seems to work.

When the different RSI methods are compared, the best results were gained with the rule using the longest 21-day period and the neutralization levels i.e. buy and sell signal levels 20 and 80. An investor employing this method would have gained abnormal profits in 49% of the cases. The figure is as high as 48% even after the transaction costs are introduced. When the RSI calculation periods are compared, also the shortest 5-day period rules performed considerably better than the original 14-day one recommended by RSI inventor Welles Wilder. When different neutralization levels are compared, on average the 70/30 rules seem to perform better.

The success of combination rules follows the success of MA and RSI rules. For example, the rule that combines the best (1,50,B) MA rule using the standard deviation band and 80/20 RSI rule using 21-day period performed best producing abnormal profits in 55% of the cases. However, the figure decreased to 47% when any trading costs were introduced. The results also show that the simultaneous use of these complementary methods isn't a great help to improve trading performance.

To evaluate how the trading rules affect the research results, the focus is again on the cases where abnormal profits have been gained in at least 50% of the simulations. With 0 trading costs, there were 10 trading rules providing profits frequently enough. These were all three different MA (1,50,B) rules and seven combination rules combining (1,50,B) MA rules to different RSI rules. It should be noticed that a combination rule employing (1,50,B) MA rule with 70/30 RSI rule using 5-day period, provided abnormal profits in more than 50% of the cases only when the standard deviation band was used. Consequently, also the trading band alteration seems to affect the results.

To be able to illustrate the trading strategy suitability for each of the primary investments, the above classification for different bands and trading costs is removed and the sums are used instead.

Table 14 Trading rule profitability classified by different primary investments
Both amounts and relative amounts of cases, when each trading strategy has gained abnormal profits, are presented. The figures include all secondary investments and periods. The effects of trading costs are ignored.

Number of series providing abnormal profits

		Hungary						Czech						Poland							All	
		Matav	Mol	Otp	Richter	Hu Portfolio	Bux	Cesky	Cez	Komerceni	Philip	Cz Portfolio	PX 50	Tpsa	Elektrim	Kghm	Pekao	Prokom	Pl Portfolio	Wig	Shr Porfolio	Ind Portfolio
MA	1:50	18	19	0	14	12	24	17	13	18	0	6	18	8	18	10	8	18	7	18	6	12
MA	1:150	18	2	0	3	0	23	11	7	18	0	1	12	9	18	15	0	17	8	12	0	11
MA	5:150	18	1	0	6	0	24	11	10	18	1	0	11	3	18	15	0	18	9	10	0	6
MA	1:200	18	0	0	5	0	24	9	6	18	0	3	18	9	18	14	0	18	9	10	0	12
MA	2:200	18	0	0	8	0	24	9	6	18	0	1	18	9	18	18	0	18	9	9	0	12
RSI 5d	30/70	5	5	0	6	0	4	3	3	1	0	0	0	3	7	5	0	6	2	6	0	4
RSI 5d	20/80	2	6	0	4	3	4	1	3	0	0	0	0	3	5	4	0	2	0	4	0	0
RSI 14d	30/70	6	5	0	4	2	4	1	9	0	0	0	0	3	5	6	0	0	0	6	0	3
RSI 14d	20/80	3	6	0	7	1	2	1	7	0	0	0	0	3	5	5	0	0	0	1	0	0
RSI 21d	30/70	4	5	2	6	6	6	3	8	2	0	2	2	3	4	2	0	0	0	2	1	4
RSI 21d	20/80	0	8	2	6	5	5	2	2	5	0	0	6	3	4	5	4	0	2	4	0	3
Combined 5d 30/70	1:50	18	16	0	8	7	24	9	14	0	0	0	5	8	17	15	0	18	9	18	3	12
Combined 5d 30/70	1:150	18	3	0	2	1	15	10	11	0	0	0	0	9	12	13	0	18	9	18	0	5
Combined 5d 30/70	5:150	18	3	0	7	1	17	10	14	0	0	0	0	9	12	9	0	16	8	17	0	6
Combined 5d 30/70	1:200	18	1	0	5	1	16	9	17	0	0	0	0	9	12	14	0	18	9	16	0	5
Combined 5d 30/70	2:200	18	1	0	5	1	15	9	16	0	0	0	0	9	12	15	0	18	9	18	0	4
Combined 5d 20/80	1:50	18	14	0	3	2	24	9	12	0	0	0	0	9	18	15	0	15	7	17	0	11
Combined 5d 20/80	1:150	18	1	0	1	1	12	9	6	0	0	0	0	9	14	15	0	18	9	13	0	0
Combined 5d 20/80	5:150	18	2	0	1	1	14	9	14	0	0	0	0	9	14	15	0	18	8	13	0	1
Combined 5d 20/80	1:200	18	1	0	1	1	10	9	6	0	0	0	0	9	13	15	0	18	9	10	0	0
Combined 5d 20/80	2:200	18	1	0	1	1	10	9	6	0	0	0	0	9	15	15	0	18	9	12	0	0
Combined 14d 30/70	1:50	18	18	0	2	1	9	11	16	0	0	0	11	9	18	14	0	12	6	18	0	12
Combined 14d 30/70	1:150	18	7	0	1	1	9	9	8	0	0	0	1	9	12	15	0	0	6	12	0	6
Combined 14d 30/70	5:150	18	8	0	1	1	6	9	10	0	0	0	0	9	12	18	0	1	3	7	0	3
Combined 14d 30/70	1:200	18	11	0	1	1	6	8	7	0	0	0	6	9	12	17	0	0	5	8	0	6
Combined 14d 30/70	2:200	18	7	0	1	1	6	8	7	0	0	0	6	9	12	18	0	0	6	6	0	5
Combined 14d 20/80	1:50	18	13	0	10	6	12	9	18	0	0	0	6	9	18	15	0	11	6	18	0	8
Combined 14d 20/80	1:150	18	8	0	9	1	4	9	17	0	0	0	2	9	12	15	0	1	6	10	0	1
Combined 14d 20/80	5:150	18	8	0	11	1	2	9	17	0	0	0	3	9	12	15	0	0	5	12	0	2
Combined 14d 20/80	1:200	18	10	0	10	1	3	9	11	0	0	0	3	9	12	14	0	16	8	10	0	2
Combined 14d 20/80	2:200	18	11	0	12	1	4	9	7	0	0	0	3	9	12	14	0	15	9	11	0	3
Combined 21d 30/70	1:50	18	16	0	9	4	20	9	21	8	0	0	18	9	12	13	0	12	6	18	0	12
Combined 21d 30/70	1:150	18	11	0	5	1	17	9	18	2	0	0	7	9	12	15	0	15	6	12	0	7
Combined 21d 30/70	5:150	18	10	0	6	1	12	9	19	1	0	0	6	9	12	14	0	2	3	12	0	6
Combined 21d 30/70	1:200	18	13	0	7	1	13	9	20	4	0	0	11	9	12	13	0	16	6	12	0	9
Combined 21d 30/70	2:200	18	10	0	11	1	11	9	18	5	0	0	9	9	12	15	0	16	6	12	0	8
Combined 21d 20/80	1:50	18	18	0	13	10	14	15	16	12	0	0	15	9	12	15	2	7	6	18	0	12
Combined 21d 20/80	1:150	18	18	0	1	1	15	9	6	18	0	0	10	9	16	15	0	6	9	12	0	5
Combined 21d 20/80	5:150	18	18	0	3	1	16	9	5	18	0	0	9	9	18	15	0	0	9	12	0	7
Combined 21d 20/80	1:200	18	15	0	1	1	17	9	6	15	0	0	10	9	18	15	0	10	9	10	0	9
Combined 21d 20/80	2:200	18	15	0	2	1	17	9	5	15	0	0	11	9	18	15	0	11	9	9	0	7
Sum		650	345	4	219	83	514	346	442	196	1	13	237	325	533	540	14	423	261	473	10	241

Percentage of series providing abnormal profits

		Hungary						Czech						Poland							All	
		Matav	Mol	Otp	Richter	Hu Portfolio	Bux	Cesky	Cez	Komerceni	Philip	Cz Portfolio	PX 50	Tpsa	Elektrim	Kghm	Pekao	Prokom	Pl Portfolio	Wig	Shr Porfolio	Ind Portfolio
MA	1:50	100	70	0	52	67	100	94	48	67	0	33	100	89	100	56	44	100	78	100	67	100
MA	1:150	100	7	0	11	0	96	61	26	67	0	6	67	100	100	83	0	94	89	67	0	92
MA	5:150	100	4	0	22	0	100	61	37	67	4	0	61	33	100	83	0	100	100	56	0	50
MA	1:200	100	0	0	19	0	100	50	22	67	0	17	100	100	100	78	0	100	100	56	0	100
MA	2:200	100	0	0	30	0	100	50	22	67	0	6	100	100	100	100	0	100	100	50	0	100
RSI 5d	30/70	83	56	0	67	0	50	50	33	11	0	0	0	100	117	83	0	100	67	100	0	100
RSI 5d	20/80	33	67	0	44	50	50	17	33	0	0	0	0	100	83	67	0	33	0	67	0	0
RSI 14d	30/70	100	56	0	44	33	50	17	100	0	0	0	0	100	83	100	0	0	0	100	0	75
RSI 14d	20/80	50	67	0	78	17	25	17	78	0	0	0	0	100	83	83	0	0	0	17	0	0
RSI 21d	30/70	67	56	22	67	100	75	50	89	22	0	33	33	100	67	33	0	0	0	33	33	100
RSI 21d	20/80	0	89	22	67	83	63	33	22	56	0	0	100	100	67	83	67	0	67	67	0	75
Combined 5d 30/70	1:50	100	59	0	30	39	100	50	52	0	0	0	28	89	94	83	0	100	100	100	33	100
Combined 5d 30/70	1:150	100	11	0	7	6	63	56	41	0	0	0	0	100	67	72	0	100	100	100	0	42
Combined 5d 30/70	5:150	100	11	0	26	6	71	56	52	0	0	0	0	100	67	50	0	89	89	94	0	50
Combined 5d 30/70	1:200	100	4	0	19	6	67	50	63	0	0	0	0	100	67	78	0	100	100	89	0	42
Combined 5d 30/70	2:200	100	4	0	19	6	63	50	59	0	0	0	0	100	67	83	0	100	100	100	0	33
Combined 5d 20/80	1:50	100	52	0	11	11	100	50	44	0	0	0	0	100	100	83	0	83	78	94	0	92
Combined 5d 20/80	1:150	100	4	0	4	6	50	50	22	0	0	0	0	100	78	83	0	100	100	72	0	0
Combined 5d 20/80	5:150	100	7	0	4	6	58	50	52	0	0	0	0	100	78	83	0	100	89	72	0	8
Combined 5d 20/80	1:200	100	4	0	4	6	42	50	22	0	0	0	0	100	72	83	0	100	100	56	0	0
Combined 5d 20/80	2:200	100	4	0	4	6	42	50	22	0	0	0	0	100	83	83	0	100	100	67	0	0
Combined 14d 30/70	1:50	100	67	0	7	6	38	61	59	0	0	0	61	100	100	78	0	67	67	100	0	100
Combined 14d 30/70	1:150	100	26	0	4	6	38	50	30	0	0	0	6	100	67	83	0	0	67	67	0	50
Combined 14d 30/70	5:150	100	30	0	4	6	25	50	37	0	0	0	0	100	67	100	0	6	33	39	0	25
Combined 14d 30/70	1:200	100	41	0	4	6	25	44	26	0	0	0	33	100	67	94	0	0	56	44	0	50
Combined 14d 30/70	2:200	100	26	0	4	6	25	44	26	0	0	0	33	100	67	100	0	0	67	33	0	42
Combined 14d 20/80	1:50	100	48	0	37	33	50	50	67	0	0	0	33	100	100	83	0	61	67	100	0	67
Combined 14d 20/80	1:150	100	30	0	33	6	17	50	63	0	0	0	11	100	67	83	0	6	67	56	0	8
Combined 14d 20/80	5:150	100	30	0	41	6	8	50	63	0	0	0	17	100	67	83	0	0	56	67	0	17
Combined 14d 20/80	1:200	100	37	0	37	6	13	50	41	0	0	0	17	100	67	78	0	89	89	56	0	17
Combined 14d 20/80	2:200	100	41	0	44	6	17	50	26	0	0	0	17	100	67	78	0	83	100	61	0	25
Combined 21d 30/70	1:50	100	59	0	33	22	83	50	78	30	0	0	100	100	67	72	0	67	67	100	0	100
Combined 21d 30/70	1:150	100	41	0	19	6	71	50	67	7	0	0	39	100	67	83	0	83	67	67	0	58
Combined 21d 30/70	5:150	100	37	0	22	6	50	50	70	4	0	0	33	100	67	78	0	11	33	67	0	50
Combined 21d 30/70	1:200	100	48	0	26	6	54	50	74	15	0	0	61	100	67	72	0	89	67	67	0	75
Combined 21d 30/70	2:200	100	37	0	41	6	46	50	67	19	0	0	50	100	67	83	0	89	67	67	0	67
Combined 21d 20/80	1:50	100	67	0	48	56	58	83	59	44	0	0	83	100	67	83	11	39	67	100	0	100
Combined 21d 20/80	1:150	100	67	0	4	6	63	50	22	67	0	0	56	100	89	83	0	33	100	67	0	42
Combined 21d 20/80	5:150	100	67	0	11	6	67	50	19	67	0	0	50	100	100	83	0	0	100	67	0	58
Combined 21d 20/80	1:200	100	56	0	4	6	71	50	22	56	0	0	56	100	100	83	0	56	100	56	0	75
Combined 21d 20/80	2:200	100	56	0	7	6	71	50	19	56	0	0	61	100	100	83	0	61	100	50	0	58
Sum		98	35	0	22	12	58	52	44	20	0	2	36	98	80	81	2	64	78	71	3	54

When the rule performance with different investments is evaluated, no consistent characteristics can be found. On average, MA rules seem to work best, but in many cases RSI rules finally bring the highest amounts of abnormal profits. However, with latter ones the abnormal profits often disappear when trading costs are introduced. Interestingly, in several cases the combination rules seem to bring the average amount of abnormal profits lower.

When the average figures are compared further, it can be noticed that MA and combination rules worked best with Matav shares gaining abnormal profits in 100% of the cases. Additionally, although not indicated by the table, after introducing the 0.5% trading costs, any of the rules brought abnormal profits in at least 89% of the cases. RSI rules worked best with Tpsa that also profited an investor in 100% of the cases. With some RSI rules, the 0.5% trading costs reduced this profitability, but the lowest figure was still 67%.

It can be seen that several equities, indices and portfolios provide conditions suitable for making abnormal profits with *all* variations of certain trading rules. For example, an investor trading actively with Matav shares may have gained abnormal profits with all variations of MA rules, almost all combination rules and 5-day RSI rules with 30/70 neutralization zones.

When the results gained with different indices are compared, it can be noticed that the best results were achieved when MA rules were applied to Bux. Abnormal profits were gained in minimum 96% of the cases and after 0.5% costs in 63% of the cases. Simultaneously both RSI and combination rules, on average, worked best when applied to Wig. However, there are remarkable differences. The weakest performing RSI rule provided abnormal profits only in 17% of the cases and all of these disappeared as soon as the 0.5% costs were applied. On the other hand, with best combination rules abnormal profits were gained in 100% of the cases even with trading costs.

In portfolios the MA and combination rules performed best with Poland portfolio. Again, the average figures are high although the differences are notable. The abnormal profits were often gained in 100% of the cases while the weakest rules were profitable only in 33% of the cases. The latter figure decreased to 0 already with lowest 0.5% trading costs. RSI rule worked exceptionally well with Hungary portfolio that usually did not profit the active trader. Although some rules produced no abnormal profits, the best rule provided profits in 100% of the cases and 50% of those disappeared after trading costs were applied.

There were only few rules bringing abnormal profits with the total share portfolio. The best rule was again (1,50,B) MA rule bringing abnormal profits in 67% of the simulations. However, this figure went down to zero as soon as the trading costs were introduced. Also with index portfolio the MA rules appeared to be the profitable ones. However, trading costs made the profits disappear and finally RSI acted as a better choice in this costly environment.

To evaluate how the trading rule selection affects the market efficiency evaluation, again the cases, where abnormal profits have been gained in at least 50% of the simulations, are highlighted. It can be noticed in previous table that in almost half of the cases the portfolio and index figures would have indicated the respective markets to be inefficient ones if the trading costs were ignored. Therefore the evaluation now concentrates on the figures gained with 0.5%, 1.0% and 2.0% trading costs, although these are not necessarily indicated by the previous tables.

The abovementioned best performing 21-day 80/20 RSI method seemed to give the best average results. When the rule was applied to Hungary, Poland or index portfolio, it indicated the respective markets to be inefficient even with 2.0% trading costs. With 1.0% trading costs also Bux and PX 50 indices proved the respective markets to be inefficient. Also 21-day 70/30 RSI rule indicated Hungarian markets to be inefficient when 0.5%-1.0% trading costs were applied. Even the popular 14-day 70/30 RSI showed Hungary and Poland markets to be inefficient if the trading costs were low enough. Other RSI rules did not produce similar results.

From MA rules again the (1.50,B) rule worked best. When applied to indices, it indicated all the markets to be inefficient with 0.5% trading costs while Bux and Wig provided enough abnormal profits even with 1.0% costs. Other MA rules were most successful with Poland portfolio and Bux index, in several cases also with 1.0% trading costs.

Combination rules worked well in Polish markets, both with share portfolio and Wig index. At least half of the rules brought abnormal profits when 0.5% trading costs were employed. The combination rules including the 21-day 80/20 RSI performed best indicating the markets to be inefficient even with 2.0% trading costs. These rules gave similar results also when applied to Bux index.

When the trading band performance is evaluated in primary investment-specific level, the results vary like mentioned earlier. The standard deviation band seems to provide best results while 1% band still gives better results than 0% band. However, there are several exceptions. Again when the cases where abnormal profits have been gained in more than 50% of the simulations are followed, it can be noticed that trading band would have changed the evaluation of market efficiency only in 2 cases. When 0.5% trading costs were introduced and the bands of standard deviation and 1% were applied to Wig index, the average results indicated inefficiency. However, the results gained with 0% band are well below 50% and thus indicated the market to be efficient. The results gained with Poland portfolio behave similarly, but now the standard deviation is the only band providing abnormal profits in less than 50% of the cases.

As a conclusion, the different rules and trading bands affect the trading results considerably and could change the interpretation of research results. However in this study they don't affect the final evaluation of market efficiency.

The trading rule performance is discussed previously in several studies and also now leaves many fascinating open questions. Especially the previously mentioned connection between market characteristics and optimal trading rules might be researched further in many ways. For example, certain statistics or even visual patterns might be used to assist in selecting the best trading rule. However, when the graphs plotted with original time series data are compared to trading rule performance presented in the table 14 above, no evident relationship can be seen. Only Tpsa graph had some characteristics typical for an antitrending series, which can be related to a trading environment suitable for RSI rules. However, additional research would be required to make any proper conclusions. The possibility to forecast the trading rule profitability and suitability is discussed further in the chapter 8.5.

8.4.3 Different Secondary Investments

To give more realistic picture on the possibilities of an active investor, different tools are used to invest the money that is received from abovementioned primary investments after a sell signal. These secondary investments are equal to 0% or 2% fixed annual interest rates or an investment in a tool imitating the development of a local market index. Applied indices are the same that have been selected to represent the average development in each market i.e. Bux, PX 50 and Wig.

The following table shows the differences in the quantities of profitable trading simulations when different secondary investments have been used.

Table 15 Trading rule profitability classified by different secondary investments
The first set of columns labeled with 0% interest rate includes the amounts of abnormal profits gained in simulations where an investor is assumed to be able to invest the sold primary investment value only with 0% profit. The second set of columns labeled with 2% interest rate refers to a situation where after selling the shares etc. the money is invested with 2% annual rate. The last columns indicate the situation where local market index has been used as a secondary investment. The columns marked with 0 show quantities of abnormal profits gained only without trading costs while >0 includes results of simulations where any trading costs have been involved. All variations related to trading bands, primary investments and periods have been summed and reported in single figures.

				Number of simulations providing abnormal profits												Percentage of simulations providing abnormal profits											
				0% interest rate			2% interest rate			Index			Sum			0% interest			2% interest			Index			Sum		
				0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum
MA			1:50	35	76	111	33	81	114	21	18	39	89	175	264	24	52	76	22	55	78	19	16	35	22	43	65
			1:150	27	42	69	28	49	77	14	25	39	69	116	185	18	29	47	19	33	52	13	23	35	17	29	46
			5:150	21	45	66	18	54	72	8	33	41	47	132	179	14	31	45	12	37	49	7	30	37	12	33	44
			1:200	24	50	74	21	58	79	10	28	38	55	136	191	16	34	50	14	39	54	9	25	34	14	34	47
			2:200	22	54	76	17	61	78	7	34	41	46	149	195	15	37	52	12	41	53	6	31	37	11	37	48
RSI	5d		30/70	20	3	23	21	4	25	11	1	12	52	8	60	41	6	47	43	8	51	30	3	32	39	6	44
			20/80	10	3	13	10	6	16	10	2	12	30	11	41	20	6	27	20	12	33	27	5	32	22	8	30
	14d		30/70	2	15	17	2	17	19	9	9	18	13	41	54	4	31	35	4	35	39	24	24	49	10	30	40
			20/80	2	10	12	3	12	15	4	10	14	9	32	41	4	20	24	6	24	31	11	27	38	7	24	30
	21d		30/70	6	18	24	3	23	26	2	10	12	11	51	62	12	37	49	6	47	53	5	27	32	8	38	46
			20/80	0	25	25	1	30	31	0	10	10	1	65	66	0	51	51	2	61	63	0	27	27	1	48	49
Combined	5d	30/70	1:50	44	34	78	47	39	86	18	19	37	109	92	201	30	23	53	32	27	59	16	17	33	27	23	50
			1:150	20	27	47	28	32	60	16	21	37	64	80	144	14	18	32	19	22	41	14	19	33	16	20	36
			5:150	26	26	52	31	29	60	14	21	35	71	76	147	18	18	35	21	20	41	13	19	32	18	19	36
			1:200	22	30	52	25	34	59	17	22	39	64	86	150	15	20	35	17	23	40	15	20	35	16	21	37
			2:200	20	31	51	23	36	59	16	24	40	59	91	150	14	21	35	16	24	40	14	22	36	15	22	37
		20/80	1:50	24	44	68	23	52	75	11	20	31	58	116	174	16	30	46	16	35	51	10	18	28	14	29	43
			1:150	15	29	44	13	36	49	7	26	33	35	91	126	10	20	30	9	24	33	6	23	30	9	22	31
			5:150	16	32	48	12	40	52	13	24	37	41	96	137	11	22	33	8	27	35	12	22	33	10	24	34
			1:200	9	33	42	8	37	45	7	26	33	24	96	120	6	22	29	5	25	31	6	23	30	6	24	30
			2:200	6	37	43	7	41	48	6	27	33	19	105	124	4	25	29	5	28	33	5	24	30	5	26	31
	14d	30/70	1:50	12	52	64	22	56	78	8	25	33	42	133	175	8	35	44	15	38	53	7	23	30	10	33	43
			1:150	13	27	40	12	33	45	8	21	29	33	81	114	9	18	27	8	22	31	7	19	26	8	20	28
			5:150	0	31	31	9	31	40	10	25	35	19	87	106	0	21	21	6	21	27	9	23	32	5	21	26
			1:200	15	24	39	11	35	46	6	24	30	32	83	115	10	16	27	7	24	31	5	22	27	8	20	28
			2:200	13	25	38	7	34	41	6	25	31	26	84	110	9	17	26	5	23	28	5	23	28	6	21	27
		20/80	1:50	27	39	66	29	49	78	14	19	33	70	107	177	18	27	45	20	33	53	13	17	30	17	26	44
			1:150	8	31	39	11	36	47	15	21	36	34	88	122	5	21	27	7	24	32	14	19	32	8	22	30
			5:150	5	34	39	6	42	48	9	28	37	20	104	124	3	23	27	4	29	33	8	25	33	5	26	31
			1:200	7	35	42	13	43	56	13	25	38	33	103	136	5	24	29	9	29	38	12	23	34	8	25	34
			2:200	4	37	41	16	41	57	7	33	40	27	111	138	3	25	28	11	28	39	6	30	36	7	27	34
	21d	30/70	1:50	34	43	77	34	59	93	12	23	35	80	125	205	23	29	52	23	40	63	11	21	32	20	31	51
			1:150	15	43	58	18	52	70	9	27	36	42	122	164	10	29	39	12	35	48	8	24	32	10	30	40
			5:150	11	34	45	14	47	61	9	25	34	34	106	140	7	23	31	10	32	41	8	23	31	8	26	35
			1:200	9	46	55	31	49	80	9	29	38	49	124	173	6	31	37	21	33	54	8	26	34	12	31	43
			2:200	8	48	56	21	53	74	11	29	40	40	130	170	5	33	38	14	36	50	10	26	36	10	32	42
		20/80	1:50	15	69	84	13	81	94	9	25	34	37	175	212	10	47	57	9	55	64	8	23	31	9	43	52
			1:150	12	45	57	12	60	72	12	27	39	36	132	168	8	31	39	8	41	49	11	24	35	9	33	41
			5:150	6	52	58	4	67	71	7	31	38	17	150	167	4	35	39	3	46	48	6	28	34	4	37	41
			1:200	14	46	60	15	61	76	12	24	36	41	131	172	10	31	41	10	41	52	11	22	32	10	32	42
			2:200	10	48	58	14	62	76	9	28	37	33	138	171	7	33	39	10	42	52	8	25	33	8	34	42
Sum				609	1473	2082	686	1762	2448	416	924	1340	1711	4159	5870	11	27	38	13	32	45	10	22	33	11	28	39

In general, the effects of secondary investments were similar with all rule types. There were some exceptions, but in most of the simulations the secondary investment equaling 2% annual interest rate profited the investor most. Naturally, the simulations, where secondary investments meant 0% interest did not perform as well as the ones employing 2% interest. However, these did bring more abnormal profits than the ones where money was invested in indices. On average, when the money was invested in market indices after sell signals, the investor actually lost money. However, there are cases where this generalization does not apply.

Like mentioned in the chapter 8.4.1, when the active trading results are compared to those gained with buy & hold strategy, the Sharpe ratios provide worthless information unless also the effects of different secondary investments are illustrated. Due to the nature of Sharpe measure calculation, a time series including periods of stable positive profit naturally provides a higher Sharpe than one gaining zero profit during same periods. Further, when a market index is used as this kind of secondary investment, the Sharpe figure is affected by higher standard deviation. The following table presents the numbers of cases, where Sharpe values after active trading exceeded Sharpes gained with the buy & hold strategy.

Table 16 Risk-adjusted trading rule performance divided to different secondary investments
Both amounts and relative amounts of the cases, when each trading strategy has gained abnormal Sharpes, are presented. The first columns labeled with 0% interest rate include amounts of abnormal Sharpes gained in simulations where an investor is assumed to be able to invest the sold primary investment value only with 0% profit. The second columns labeled with 2% interest rate refer to a situation where after selling the shares etc. the money is invested with 2% annual rate. The last columns indicate the situation where local market index has been used as a secondary investment. The figures include all trading band variations, primary investments and periods.

				Number of simulations providing abnormal Sharpes				Percentage of simulations providing abnormal Sharpes			
				0% interest	2% interest	Index	Sum	0% interest	2% interest	Index	Sum
MA			1:50	125	128	44	297	85%	87%	40%	73%
			1:150	66	72	41	179	45%	49%	37%	44%
			5:150	63	70	40	173	43%	48%	36%	43%
			1:200	70	79	42	191	48%	54%	38%	47%
			2:200	69	76	43	188	47%	52%	39%	46%
RSI	5d		30/70	19	23	11	53	39%	47%	30%	39%
			20/80	8	11	6	25	16%	22%	16%	19%
	14d		30/70	17	18	19	54	35%	37%	51%	40%
			20/80	14	15	14	43	29%	31%	38%	32%
	21d		30/70	22	23	16	61	45%	47%	43%	45%
			20/80	24	27	12	63	49%	55%	32%	47%
Combined	5d	30/70	1:50	89	104	34	227	61%	71%	31%	56%
			1:150	49	57	36	142	33%	39%	32%	35%
			5:150	52	62	35	149	35%	42%	32%	37%
			1:200	64	73	42	179	44%	50%	38%	44%
			2:200	64	75	43	182	44%	51%	39%	45%
		20/80	1:50	77	87	38	202	52%	59%	34%	50%
			1:150	39	54	35	128	27%	37%	32%	32%
			5:150	32	50	29	111	22%	34%	26%	27%
			1:200	35	47	29	111	24%	32%	26%	27%
			2:200	38	51	35	124	26%	35%	32%	31%
	14d	30/70	1:50	63	84	35	182	43%	57%	32%	45%
			1:150	16	26	33	75	11%	18%	30%	19%
			5:150	14	33	32	79	10%	22%	29%	20%
			1:200	10	31	32	73	7%	21%	29%	18%
			2:200	11	32	31	74	7%	22%	28%	18%
		20/80	1:50	46	74	37	157	31%	50%	33%	39%
			1:150	20	41	34	95	14%	28%	31%	23%
			5:150	30	39	42	111	20%	27%	38%	27%
			1:200	17	46	36	99	12%	31%	32%	24%
			2:200	17	36	36	89	12%	24%	32%	22%
	21d	30/70	1:50	76	95	31	202	52%	65%	28%	50%
			1:150	32	64	38	134	22%	44%	34%	33%
			5:150	29	51	34	114	20%	35%	31%	28%
			1:200	47	71	39	157	32%	48%	35%	39%
			2:200	39	67	38	144	27%	46%	34%	36%
		20/80	1:50	84	100	34	218	57%	68%	31%	54%
			1:150	40	64	38	142	27%	44%	34%	35%
			5:150	43	65	36	144	29%	44%	32%	36%
			1:200	43	59	29	131	29%	40%	26%	32%
			2:200	43	63	36	142	29%	43%	32%	35%
Sum				1756	2343	1345	5444	32%	43%	33%	36%

Again, the average effects of secondary investments were similar with all rule types. It can be noticed that in some cases the aforementioned generalization does not apply. The secondary investments in the market indices have sometimes profited enough to compensate the related standard deviation and to give a Sharpe measure higher than the one gained with 0% interest.

Now the effects of secondary investments are presented also in primary investment-specific level. Table 17 presents first the abnormal profits of each share, index and portfolio.

Table 17 Trading results classified by primary investments and secondary investments
Both amounts and relative amounts of the cases, when abnormal profits have been gained, are presented. The first set of columns labeled with 0% interest rate includes amounts of abnormal profits gained in simulations where an investor is assumed to be able to invest the sold primary investment value only with 0% profit. The second set of columns labeled with 2% interest rate refers to a situation where after selling the shares etc. the money is invested with 2% annual rate. The last columns indicate the situation where local market index has been used as a secondary investment. When primary investment has been a market index, only 0% and 2% interests have acted as possible secondary investments. The columns marked with 0 show quantities of abnormal profits gained only without trading costs while >0 includes results of simulations where 0.5% trading costs have been involved. The figures include all rule variations and periods.

	Primary investment	Number of simulations providing abnormal profits												Percentage of simulations providing abnormal profits											
		0% interest rate			2% interest rate			Index			Sum			0% interest			2% interest			Index			Sum		
		0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum	0	>0	Sum
Hungary	Matav	4	212	216	3	213	216	9	209	218	16	634	650	2	95	97	1	96	97	4	94	98	2	95	98
	Mol	49	45	94	65	61	126	64	61	125	178	167	345	15	14	28	20	18	38	19	18	38	18	17	35
	Otp	1	1	2	0	2	2	0	0	0	1	3	4	0	0	1	0	1	1	0	0	0	0	0	0
	Richter	34	29	63	47	42	89	51	16	67	132	87	219	10	9	19	14	13	27	15	5	20	13	9	22
	Portfolio	16	3	19	22	6	28	35	1	36	73	10	83	7	1	9	10	3	13	16	0	16	11	2	12
	Bux	102	125	227	108	179	287	0	0	0	210	304	514	23	28	51	24	40	65	-	-	-	24	34	58
Czech	Cesky	8	104	112	13	108	121	14	99	113	35	311	346	4	47	50	6	49	55	6	45	51	5	47	52
	Cez	78	78	156	71	109	180	97	9	106	246	196	442	23	23	47	21	33	54	29	3	32	25	20	44
	Komercni	6	62	68	15	63	78	16	34	50	37	159	196	2	19	20	5	19	23	5	10	15	4	16	20
	Philip	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	Portfolio	5	0	5	6	1	7	1	0	1	12	1	13	2	0	2	3	0	3	0	0	0	2	0	2
	PX 50	49	34	83	74	80	154	0	0	0	123	114	237	15	10	25	22	24	46	-	-	-	18	17	36
Poland	Tpsa	0	109	109	0	109	109	21	86	107	21	304	325	0	98	98	0	98	98	19	77	96	6	91	98
	Elektrim	16	133	149	21	143	164	11	209	220	48	485	533	7	60	67	9	64	74	5	94	99	7	73	80
	Kghm	41	159	200	41	176	217	12	111	123	94	446	540	18	72	90	18	79	98	5	50	55	14	67	81
	Pekao	3	2	5	7	2	9	0	0	0	10	4	14	1	1	2	3	1	4	0	0	0	2	1	2
	Prokom	28	118	146	24	134	158	41	78	119	93	330	423	13	53	66	11	60	71	18	35	54	14	50	64
	Portfolio	29	70	99	17	90	107	44	11	55	90	171	261	26	63	89	15	81	96	40	10	50	27	51	78
	Wig	70	158	228	60	185	245	0	0	0	130	343	473	21	47	68	18	56	74	-	-	-	20	52	71
All	Shr Portfolio	3	0	3	7	0	7	0	0	0	10	0	10	3	0	3	6	0	6	0	0	0	3	0	3
	Ind Portfolio	67	31	98	84	59	143	0	0	0	151	90	241	30	14	44	38	27	64	-	-	-	34	20	54
Sum		609	1473	2082	686	1762	2448	416	924	1340	1711	4159	5870	11	27	38	13	32	45	10	22	33	11	28	39

Now the effects of different secondary investments can be compared again from a different angle. Generally, the secondary investments don't change the results too much. Naturally 2% fixed rate profited more frequently than 0%, but the difference was not remarkable. However, when an index was used as a secondary investment tool, the profits differed sometimes considerably from the ones gained with fixed rates. Sometimes an investment in an index improved the trading success, but in most cases also the index value has obviously decreased after the trading rules have given a sell signal indicating also the underlying share value to decrease. This obviously depends on the correlation between the share and the respective market index, indicated also by the share's beta value.

Now also the Sharpe ratios for different primary investments can be compared more accurately as the effects of secondary investments, acting as possible causes for abnormal Sharpes, can be highlighted.

Table 18 Risk-adjusted trading results classified by primary investments and secondary investments
Both amounts and relative amounts of the cases, when abnormal Sharpes have been gained, are presented. The first columns labeled with 0% interest include amounts of abnormal Sharpes gained in simulations where an investor is assumed to be able to invest the sold primary investment value only with 0% profit. The second columns labeled with 2% interest refer to a situation where after selling the shares etc. the money is invested with 2% annual rate. The last columns indicate the situation where local market index has been as a secondary investment. The figures include all rule variations and periods.

	Primary investment	Number of simulations providing abnormal Sharpes				Percentage of simulations providing abnormal Sharpes			
		0% interest	2% interest	Index	Sum	0% interest	2% interest	Index	Sum
Hungary	Matav	107	155	214	476	48%	70%	96%	71%
	Mol	63	72	122	257	19%	22%	37%	26%
	Otp	6	6	0	12	2%	2%	0%	1%
	Richter	132	171	84	387	40%	51%	25%	39%
	Portfolio	32	43	3	78	14%	19%	1%	12%
	Bux	207	282	-	489	47%	64%	-	55%
Czech	Cesky	75	109	62	246	34%	49%	28%	37%
	Cez	107	147	33	287	32%	44%	10%	29%
	Komercni	95	116	46	257	29%	35%	14%	26%
	Philip	10	20	0	30	3%	6%	0%	3%
	Portfolio	130	166	143	439	59%	75%	64%	66%
	PX 50	108	168	-	276	32%	50%	-	41%
Poland	Tpsa	63	72	50	185	57%	65%	45%	56%
	Elektrim	89	106	203	398	40%	48%	91%	60%
	Kghm	61	83	82	226	27%	37%	37%	34%
	Pekao	42	49	0	91	19%	22%	0%	14%
	Prokom	104	118	85	307	47%	53%	38%	46%
	Portfolio	72	81	107	260	65%	73%	96%	78%
	Wig	115	142	-	257	35%	43%	-	39%
All	Shr Portfolio	56	84	111	251	50%	76%	100%	75%
	Ind Portfolio	82	153	-	235	37%	69%	-	53%
	Sum	1756	2343	1345	5444	32%	43%	33%	36%

The Sharpe figures follow the profit figures reported in table 17 as some profitably traded shares and indices provided also high amounts of abnormal Sharpes. However, now the secondary investments do change the results considerably. Although the associated risk level decreased the Sharpes, some series e.g. Matav provided highest amounts of abnormal Sharpes when the index was used as a secondary investment. The relevance of risk levels can also be seen in the abnormal Sharpe figures of Czech, Poland and total share portfolio as diversified risk leads usually to high Sharpe figures. However, Hungary portfolio acted as a peculiar exception as this provided the third lowest number of abnormal Sharpe figures.

To define how the secondary investments affect the assessment of market efficiency, the rules or primary investments bringing abnormal profits or abnormal Sharpes in at least 50% of the cases are again screened. When the results were classified by the trading rules, enough abnormal profits were gained in 16 of the cases when secondary investment meant investing with fixed 2% annual interest. The figure was only 6 with 0% interest and 0 with index. However, when the trading costs were also involved, already 0.5% costs decreased the profit frequencies to 3, 2 and 0. With Sharpes the respective figures were similar i.e. 12, 5 and 1.

When the results were classified by the primary investments, fixed 2% annual interest brought enough abnormal profits in 11 of the cases. The figure is 9 with 0% interest and 7 with index. However, when the effect of trading costs is added, already 0.5% costs decrease the profit frequencies to 7, 6 and 4. With Sharpes the respective figures are again similar i.e. 10, 4 and 9.

If Poland portfolio was used as a primary investment and index as a secondary investment, after 0.5% trading costs abnormal profits were gained only rarely, while 2% and 0% interest rates brought abnormal profits in at least 63% of the cases. With Wig the only secondary investment exceeding the 50% limit was 2% interest when any trading costs were involved. With Sharpe measures, the sensitive primary investments were the Bux index, PX 50 index and index portfolio that provided above 50% figures only with 2% interest.

It can be concluded that secondary investments do affect the trading success, but in a costly trading environment the differences are considerably smaller. Still, secondary investment can act as a critical factor shaping the market efficiency evaluation.

8.4.4 Different Periods

Trading and buy & hold strategy successes of different equities have been evaluated on 1-3 different periods while indices have been evaluated on 3-4 periods and portfolios on 1-2 periods. The longest period always describes the time series development since the beginning while the shorter periods are fixed to be able to compare different investments to each other. The chapter 7.5.4 described the different investment periods together with their start and end dates in more detail.

The following tables 19 and 20 list the trading success in each period. These amounts of abnormal profits are again sum figures including all trading rule variations and secondary investments.

Table 19 Trading results on the shortest periods 1 and 2

The table shows the amounts of different trading simulations providing abnormal profits and abnormal Sharpes on both shortest periods separately. The trading results have been classified by shares, indices or portfolios. Both amounts and relative amounts of the cases, when simulations have gained abnormal profits and abnormal Sharpes, are presented. The columns marked with 0 show quantities of abnormal profits gained only without trading costs while >0 includes results of simulations where 0.5% trading costs have been involved. The figures include all trading rules, rule variations and secondary investments.

	Primary investment	Period 1								Period 2							
		Number of cases providing abnormal profits			Percentage of cases providing abnormal profits			Abnormal Sharpe ratios		Number of cases providing abnormal profits			Percentage of cases providing abnormal profits			Abnormal Sharpe ratios	
		0	>0	Sum	0	>0	Sum	Qty.	%	0	>0	Sum	0	>0	Sum	Qty.	%
Hungary	Matav	6	318	324	1.8	95.5	97.3	238	71.5	10	316	326	3.0	94.9	97.9	238	71.5
	Mol	103	90	193	30.9	27.0	58.0	117	35.1	71	75	146	21.3	22.5	43.8	109	32.7
	Otp	0	0	0	0.0	0.0	0.0	2	0.6	1	3	4	0.3	0.9	1.2	8	2.4
	Richter	23	23	46	6.9	6.9	13.8	94	28.2	70	59	129	21.0	17.7	38.7	98	29.4
	Portfolio	12	3	15	3.6	0.9	4.5	34	10.2	61	7	68	18.3	2.1	20.4	44	13.2
	Bux	50	61	111	22.5	18.3	40.8	102	45.9	73	80	153	32.9	24.0	56.9	115	51.8
Czech	Cesky	22	302	324	6.6	90.7	97.3	144	43.2	13	9	22	3.9	2.7	6.6	102	30.6
	Cez	9	4	13	2.7	1.2	3.9	48	14.4	107	50	157	32.1	15.0	47.1	109	32.7
	Komercni	3	0	3	0.9	0.0	0.9	44	13.2	15	82	97	4.5	24.6	29.1	103	30.9
	Philip	1	0	1	0.3	0.0	0.3	17	5.1	0	0	0	0.0	0.0	0.0	2	0.6
	Portfolio	1	1	2	0.3	0.3	0.6	136	40.8	11	0	11	3.3	0.0	3.3	303	91.0
	PX 50	42	57	99	18.9	17.1	36	92	41.4	44	26	70	19.8	7.8	27.6	72	32.4
Poland	Tpsa	21	304	325	6.3	91.3	97.6	185	55.6	21	304	325	6.3	91.3	97.6	185	55.6
	Elektrim	2	331	333	0.6	99.4	100.0	258	77.5	2	331	333	0.6	99.4	100.0	258	77.5
	Kghm	16	313	329	4.8	94.0	98.8	184	55.3	16	313	329	4.8	94.0	98.8	184	55.3
	Pekao	7	2	9	2.1	0.6	2.7	50	15.0	7	2	9	2.1	0.6	2.7	50	15.0
	Prokom	51	135	186	15.3	40.5	55.9	142	42.6	51	135	186	15.3	40.5	55.9	142	42.6
	Portfolio	90	171	261	27.0	51.4	78.4	260	78.1	90	171	261	27.0	51.4	78.4	260	78.1
	Wig	68	134	202	30.6	40.2	70.9	77	34.7	68	134	202	30.6	40.2	70.9	77	34.7
All	Shr Portfolio	10	0	10	3.0	0.0	3.0	251	75.4	-	-	-	-	-	-	-	-
	Ind Portfolio	85	66	151	38.3	19.8	58.1	71	32.0	85	66	151	38.3	19.8	58.1	71	32.0
Sum		622	2315	2937	9.5	35.3	44.8	2546	38.9	816	2163	2979	13.1	34.8	47.9	2530	40.7

Table 20 Trading results on the longest periods 3 and 4

The table shows the amounts of different trading simulations providing abnormal profits and abnormal Sharpes on both longest periods separately. The trading results have been classified by shares, indices or portfolios. Both amounts and relative amounts of the cases, when simulations have gained abnormal profits and abnormal Sharpes, are presented. The columns marked with 0 show quantities of abnormal profits gained only without trading costs while >0 includes results of simulations where 0.5% trading costs have been involved. The figures include all trading rules, rule variations and secondary investments.

	Primary investment	Period 3								Period 4							
		Number of cases providing abnormal profits			Percentage of cases providing abnormal profits			Abnormal Sharpe ratios		Number of cases providing abnormal profits			Percentage of cases providing abnormal profits			Abnormal Sharpe ratios	
		0	>0	Sum	0	>0	Sum	Qty.	%	0	>0	Sum	0	>0	Sum	Qty.	%
Hungary	Matav	10	316	326	3.0	94.9	97.9	238	71.5	-	-	-	-	-	-	-	-
	Mol	4	2	6	1.2	0.6	1.8	31	9.3	-	-	-	-	-	-	-	-
	Otp	0	0	0	0.0	0.0	0.0	2	0.6	-	-	-	-	-	-	-	-
	Richter	39	5	44	11.7	1.5	13.2	195	58.6	-	-	-	-	-	-	-	-
	Bux	63	138	201	28.4	41.4	69.8	121	54.5	24	25	49	10.8	7.5	18.3	151	68.0
Czech	Cesky	13	9	22	3.9	2.7	6.6	102	30.6	-	-	-	-	-	-	-	-
	Cez	130	142	272	39	42.6	81.7	130	39.0	-	-	-	-	-	-	-	-
	Komercni	19	77	96	5.7	23.1	28.8	110	33.0	-	-	-	-	-	-	-	-
	Philip	0	0	0	0.0	0.0	0.0	11	3.3	-	-	-	-	-	-	-	-
	PX 50	37	31	68	16.7	9.3	26	112	50.5	37	31	68	16.7	9.3	26	112	50.5
Poland	Tpsa	21	304	325	6.3	91.3	97.6	185	55.6	-	-	-	-	-	-	-	-
	Elektrim	46	154	200	13.8	46.2	60.1	140	42.0	-	-	-	-	-	-	-	-
	Kghm	78	133	211	23.4	39.9	63.4	42	12.6	-	-	-	-	-	-	-	-
	Pekao	3	2	5	0.9	0.6	1.5	41	12.3	-	-	-	-	-	-	-	-
	Prokom	42	195	237	12.6	58.6	71.2	165	49.5	-	-	-	-	-	-	-	-
	Wig	43	27	70	19.4	8.1	27.5	72	32.4	19	182	201	8.6	54.7	63.2	108	48.6
	Ind Portfolio	66	24	90	29.7	7.2	36.9	164	73.9	-	-	-	-	-	-	-	-
Sum		614	1559	2173	11.8	29.9	41.7	1861	35.7	80	238	318	12.0	35.7	47.7	371	55.7

It can be noticed that the quantities of abnormal profits vary considerably between the two longest and two shortest periods. 13 primary investments have brought greatest number of abnormal profits on the shortest period starting on 24/8/1999. 6 of the primary investments brought abnormal profits most frequently on period 2 starting on the day the latest share from the respective market was issued. Only 2 of the primary investments provided best results during longer period 3.

Second obvious point concerns the similarity of average results on periods 1 and 2. Naturally, one of the reasons is that the periods 1 and 2 are the same for all Polish equities, index and portfolio. These results don't support the earlier suggestions that markets would have generally become more efficient, which would mean that the investors, who started the active trading soon after the exchange re-openings, should have gained more abnormal profits than the ones trading only for the past few years.

Also the quantities of abnormal Sharpes vary considerably between the periods, but they also differ from the amounts of abnormal profits. The Sharpes seem to favor also the longer periods. Again, most i.e. 11 primary investments provided greatest number of abnormal Sharpes on the shortest period but the figure on period 2 was only 3. The period 3 figure was now 5 and interestingly all 3 indices favored period 4 starting on the day each index was published.

The following table shows how the results behave when also the success of different trading rules has been divided for different periods.

Table 21 Trading rule profitability classified by different periods

The basic rules are presented in different rows and categorized in classes of MA, RSI and combination rules. Both amounts and relative amounts of the cases, when each trading strategy has gained abnormal profits, are presented. The columns marked with 0 show profits without trading costs while >0 includes results gained with trading costs of 0.5%. The figures include all rule variations, primary investments and secondary investments.

			Quantity of abnormal profits									Percentage of abnormal profits									Quantity of abnormal Sharpes					Percentage of abnormal Sharpes				
			Period1		Period2		Period3		Period4		All	Period1		Period2		Period3		Period4		All	Period1	Period2	Period3	Period4	All	Period1	Period2	Period3	Period4	All
			0	>0	0	>0	0	>0	0	>0		0	>0	0	>0	0	>0	0	>0											
MA		1:50	37	74	41	89	27	68	1	17	354	20.9	41.8	24.4	53.0	19.1	48.2	5.6	94.4	70.2	127	132	107	18	384	71.8	78.6	75.9	100.0	76.2
		1:150	25	57	31	58	32	45	9	8	265	14.1	32.2	18.5	34.5	22.7	31.9	50.0	44.4	52.6	76	73	65	18	232	42.9	43.5	46.1	100.0	46.0
		5:150	18	59	26	57	20	50	3	12	245	10.2	33.3	15.5	33.9	14.2	35.5	16.7	66.7	48.6	76	66	58	18	218	42.9	39.3	41.1	100.0	43.3
		1:200	27	57	22	66	25	54	4	14	269	15.3	32.2	13.1	39.3	17.7	38.3	22.2	77.8	53.4	84	78	67	18	247	47.5	46.4	47.5	100.0	49.0
		2:200	19	65	12	73	27	59	2	16	273	10.7	36.7	7.1	43.5	19.1	41.8	11.1	88.9	54.2	81	77	70	18	246	45.8	45.8	49.6	100.0	48.8
RSI	5d	30/70	27	5	21	5	20	3	0	2	83	45.8	8.5	37.5	8.9	42.6	6.4	0.0	33.3	49.4	34	27	9	2	72	57.6	48.2	19.1	33.3	42.9
		20/80	8	7	16	7	12	3	2	0	55	13.6	11.9	28.6	12.5	25.5	6.4	33.3	0.0	32.7	8	17	6	0	31	13.6	30.4	12.8	0.0	18.5
	14d	30/70	5	20	3	23	6	14	0	2	73	8.5	33.9	5.4	41.1	12.8	29.8	0.0	33.3	43.5	29	26	16	0	71	49.2	46.4	34.0	0.0	42.3
		20/80	4	14	3	20	1	12	1	0	55	6.8	23.7	5.4	35.7	2.1	25.5	16.7	0.0	32.7	25	23	9	0	57	42.4	41.1	19.1	0.0	33.9
	21d	30/70	6	28	3	25	3	11	0	2	78	10.2	47.5	5.4	44.6	6.4	23.4	0.0	33.3	46.4	36	26	9	0	71	61.0	46.4	19.1	0.0	42.3
		20/80	0	30	0	35	1	18	0	4	88	0.0	50.8	0.0	62.5	2.1	38.3	0.0	66.7	52.4	32	37	13	2	84	54.2	66.1	27.7	33.3	50.0
Combined	5d 30/70	1:50	31	61	50	54	36	30	7	6	275	17.5	34.5	29.8	32.1	25.5	21.3	38.9	33.3	54.6	100	114	75	16	305	56.5	67.9	53.2	88.9	60.5
		1:150	25	53	31	44	29	28	0	6	216	14.1	29.9	18.5	26.2	20.6	19.9	0.0	33.3	42.9	70	56	54	10	190	39.5	33.3	38.3	55.6	37.7
		5:150	30	48	46	36	24	28	0	6	218	16.9	27.1	27.4	21.4	17.0	19.9	0.0	33.3	43.3	69	56	50	12	187	39.0	33.3	35.5	66.7	37.1
		1:200	15	56	31	48	31	30	0	6	217	8.5	31.6	18.5	28.6	22.0	21.3	0.0	33.3	43.1	85	75	65	14	239	48.0	44.6	46.1	77.8	47.4
		2:200	15	58	27	50	29	34	0	6	219	8.5	32.8	16.1	29.8	20.6	24.1	0.0	33.3	43.5	88	76	66	15	245	49.7	45.2	46.8	83.3	48.6
	5d 20/80	1:50	13	70	20	65	27	37	6	6	244	7.3	39.5	11.9	38.7	19.1	26.2	33.3	33.3	48.4	93	101	62	12	268	52.5	60.1	44.0	66.7	53.2
		1:150	14	57	16	50	16	35	1	6	195	7.9	32.2	9.5	29.8	11.3	24.8	5.6	33.3	38.7	63	68	50	11	192	35.6	40.5	35.5	61.1	38.1
		5:150	17	57	26	47	13	40	0	6	206	9.6	32.2	15.5	28.0	9.2	28.4	0.0	33.3	40.9	50	56	37	12	155	28.2	33.3	26.2	66.7	30.8
		1:200	5	62	11	54	13	36	0	6	187	2.8	35.0	6.5	32.1	9.2	25.5	0.0	33.3	37.1	50	60	42	12	164	28.2	35.7	29.8	66.7	32.5
		2:200	6	63	12	55	7	44	0	6	193	3.4	35.6	7.1	32.7	5.0	31.2	0.0	33.3	38.3	56	66	49	12	183	31.6	39.3	34.8	66.7	36.3
	14d 30/70	1:50	9	75	21	66	18	51	3	6	249	5.1	42.4	12.5	39.3	12.8	36.2	16.7	33.3	49.4	90	89	59	18	256	50.8	53.0	41.8	100.0	50.8
		1:150	16	54	16	45	5	35	5	1	177	9.0	30.5	9.5	26.8	3.5	24.8	27.8	5.6	35.1	40	38	29	3	110	22.6	22.6	20.6	16.7	21.8
		5:150	10	54	10	42	4	42	1	0	163	5.6	30.5	6.0	25.0	2.8	29.8	5.6	0.0	32.3	42	38	29	3	112	23.7	22.6	20.6	16.7	22.2
		1:200	20	54	14	45	4	38	2	0	177	11.3	30.5	8.3	26.8	2.8	27.0	11.1	0.0	35.1	49	37	21	3	110	27.7	22.0	14.9	16.7	21.8
		2:200	18	54	12	45	4	39	0	0	172	10.2	30.5	7.1	26.8	2.8	27.7	0.0	0.0	34.1	48	35	26	3	112	27.1	20.8	18.4	16.7	22.2
	14d 20/80	1:50	16	57	35	58	30	39	2	6	243	9.0	32.2	20.8	34.5	21.3	27.7	11.1	33.3	48.2	59	85	59	13	216	33.3	50.6	41.8	72.2	42.9
		1:150	8	55	22	45	8	34	0	6	178	4.5	31.1	13.1	26.8	5.7	24.1	0.0	33.3	35.3	41	54	46	3	144	23.2	32.1	32.6	16.7	28.6
		5:150	6	60	13	57	6	34	0	6	182	3.4	33.9	7.7	33.9	4.3	24.1	0.0	33.3	36.1	52	58	40	2	152	29.4	34.5	28.4	11.1	30.2
		1:200	12	64	15	59	13	34	1	5	203	6.8	36.2	8.9	35.1	9.2	24.1	5.6	27.8	40.3	46	52	44	2	144	26.0	31.0	31.2	11.1	28.6
		2:200	14	63	13	62	7	41	1	5	206	7.9	35.6	7.7	36.9	5.0	29.1	5.6	27.8	40.9	43	50	39	0	132	24.3	29.8	27.7	0.0	26.2
	21d 30/70	1:50	28	64	35	64	23	47	11	6	278	15.8	36.2	20.8	38.1	16.3	33.3	61.1	33.3	55.2	85	89	64	16	254	48.0	53.0	45.4	88.9	50.4
		1:150	21	69	21	61	6	48	2	6	234	11.9	39.0	12.5	36.3	4.3	34.0	11.1	33.3	46.4	53	55	49	9	166	29.9	32.7	34.8	50.0	32.9
		5:150	17	65	18	51	7	36	0	6	200	9.6	36.7	10.7	30.4	5.0	25.5	0.0	33.3	39.7	46	42	41	9	138	26.0	25.0	29.1	50.0	27.4
		1:200	19	73	24	65	11	45	2	6	245	10.7	41.2	14.3	38.7	7.8	31.9	11.1	33.3	48.6	64	59	58	13	194	36.2	35.1	41.1	72.2	38.5
		2:200	10	79	22	67	11	45	0	6	240	5.6	44.6	13.1	39.9	7.8	31.9	0.0	33.3	47.6	57	55	51	11	174	32.2	32.7	36.2	61.1	34.5
	21d 20/80	1:50	12	76	23	88	13	65	0	12	289	6.8	42.9	13.7	52.4	9.2	46.1	0.0	66.7	57.3	102	110	66	10	288	57.6	65.5	46.8	55.6	57.1
		1:150	11	69	18	67	15	47	4	8	239	6.2	39.0	10.7	39.9	10.6	33.3	22.2	44.4	47.4	75	74	41	8	198	42.4	44.0	29.1	44.4	39.3
		5:150	5	81	9	76	6	50	2	8	237	2.8	45.8	5.4	45.2	4.3	35.5	11.1	44.4	47.0	76	68	34	8	186	42.9	40.5	24.1	44.4	36.9
		1:200	14	71	14	68	13	55	4	4	243	7.9	40.1	8.3	40.5	9.2	39.0	22.2	22.2	48.2	70	65	40	8	183	39.5	38.7	28.4	44.4	36.3
		2:200	9	77	13	71	11	55	4	4	244	5.1	43.5	7.7	42.3	7.8	39.0	22.2	22.2	48.4	76	67	46	9	198	42.9	39.9	32.6	50.0	39.3
Sum			622	2315	816	2163	614	1559	80	238	8407	9.5	35.3	13.1	34.8	11.8	29.9	12.0	35.7	45.1	2546	2530	1861	371	7308	38.9	40.7	35.7	55.7	39.2

Naturally also the success of trading rules varies between different periods. MA rules have succeeded quite equally between periods 1-3, although the average performance decreased slightly when MA rules were applied to more recent data. However, on period 4 these have been most successful rules providing profits in 95% of the cases. The figure is as high as 74% even with 0.5% trading costs. Conversely, the average performance of RSI and combination rules improved, when those were applied to more recent data. However, the figures were usually below 50% and the differences between periods were not so clear.

When the trading success in different periods is measured with relative amounts of abnormal Sharpe ratios, the results are similar to the ones achieved with profit figures. MA rules provided again more abnormal profits on longer and RSI rules on shorter periods. However, with combination rules, the figures seem to behave more randomly without any clear characteristic.

The MA results are interesting for two reasons. Firstly, a research applying only Brock et al. (1992) MA rules just to these three major indices, might have provided results indicating all the markets to be inefficient. Secondly, the weakening performance of MA rules is the only evidence of the phenomenon that markets should adopt all the exploitable inefficiencies. If market participants have realized MA possibilities in market behavior predicting, the information should have spread to average investors and the decreased profits could be interpreted as a result of increased efficiency.

To demonstrate how the period selection affects the evaluation of market efficiency further, again the cases, where abnormal profits or abnormal Sharpes have been gained in at least 50% of the simulations, are highlighted. On period 1 enough abnormal profits were gained with only one rule. On period 2 the figure was 3. The periods 3 and 4 provided interesting results as enough abnormal profits were gained with 0 and 8 rules. Enough abnormal Sharpes were gained more frequently as the figures for periods 1, 2, 3 and 4 were 8, 8, 2 and 24. The last figure again indicates that a research employing the selected trading rules to complete index data and measuring the trading results with Sharpe measures, would have indicated all the markets to be inefficient.

When the profits and Sharpes were classified by the primary investments, no common characteristics were found. Both Bux index and index portfolio gave different evaluation on different periods with both monetary profit and Sharpe ratio. For example, without trading costs Bux index indicated the market to be inefficient only on periods 2 and 3 while the Sharpe ratios indicated the market to be efficient only on the shortest period. When the performance was measured only with Sharpe figures also Czech portfolio and PX 50 index gave different indications on market efficiency. The portfolio indicated inefficiency only on the longer period 2, while the index gave figures above 50% on two longest periods. Although abnormal profits of Wig index would have interpreted the Polish market to be an inefficient one during all periods, this was only without trading costs. 0.5% trading costs indicated the market to be inefficient only on the longest period.

The varying figures can be seen as natural consequences of changing market characteristics. To make conclusions on these market characteristics, the weaker average performance on more recent periods could be seen as a result of improved market efficiency. However, this logic is annulled by the fact that during the most recent periods the highest amounts of abnormal profits were made with rules outperforming already on period 4.

8.5 Additional Considerations

This chapter provides some additional information that is not relevant for market efficiency evaluation but evaluates the possibilities to improve the methodology and demonstrates the possibilities of technical analysis. First the trading profit levels are discussed. The table 22 below shows the average profit of each primary investment and illustrates how the different trading cost levels affect these figures.

Table 22 Average trading profits classified by different primary investments and trading costs
The profit figures indicate the change in investment value as percentages of initial investment.

	Primary investment	Average series profit (as % of initial investment)							
		0	0.5	1.0	1.5	2.0	2.5	3.0	3.5
Hungary	Matav	-2.0	-14.8	-25.3	-34.0	-41.3	-47.4	-54.1	-58.7
	Mol	2.4	-18.8	-34.1	-45.5	-54.4	-61.3	-66.8	-71.2
	Otp	36.8	0.3	-23.2	-39.1	-50.5	-58.9	-65.3	-70.2
	Richter	94.4	43.1	11.5	-10.1	-25.5	-37.1	-45.9	-53.0
	Hu Portfolio	1.5	-16.6	-29.7	-39.8	-47.9	-54.4	-59.7	-64.1
	Bux	-8.0	-25.1	-38.7	-48.9	-56.7	-64.6	-69.7	-73.8
Czech	Cesky	20.2	-10.4	-31.3	-46.0	-56.7	-64.6	-70.6	-75.2
	Cez	70.5	35.6	10.1	-8.6	-23.1	-34.6	-43.7	-51.0
	Komercni	40.3	7.1	-15.8	-30.9	-42.5	-51.0	-57.5	-62.8
	Philip	28.2	2.3	-17.0	-31.0	-41.8	-50.2	-56.9	-62.3
	Cz Portfolio	-18.9	-31.7	-41.0	-48.8	-56.8	-62.4	-67.1	-71.2
	PX 50	103.2	50.7	18.3	-3.9	-19.8	-31.7	-40.9	-48.1
Poland	Tpsa	-16.7	-27.7	-36.7	-43.9	-49.8	-54.6	-60.4	-63.9
	Elektrim	23.4	4.7	-9.3	-20.3	-29.2	-36.4	-42.3	-47.4
	Kghm	14.8	-1.2	-14.2	-24.8	-33.6	-41.0	-47.3	-52.6
	Pekao	-4.1	-16.2	-25.9	-34.0	-40.8	-46.5	-51.4	-57.2
	Prokom	74.9	31.3	3.1	-16.3	-30.3	-40.8	-48.9	-55.3
	Pl Portfolio	11.8	-8.2	-22.9	-33.9	-42.5	-49.3	-54.8	-59.3
	Wig	127.0	40.0	-5.3	-31.6	-48.0	-58.9	-66.4	-72.0
All	Shr Portfolio	10.7	-8.4	-22.9	-33.9	-42.5	-50.7	-56.4	-61.1
	Ind Portfolio	2.7	-11.2	-22.7	-32.1	-39.9	-46.4	-51.8	-56.4
	Sum	29.2	1.2	-17.8	-31.3	-41.6	-49.7	-56.1	-61.3

The average profit of simulated investments was 29.2% when trading costs were ignored. However, the costly environment decreased trading success and this average quickly from positive to negative. Extreme cases in the following table give an alternative approach to the scenarios of an investor.

Table 23 Highest profits and losses classified by primary investments and trading costs
The profit figures indicate the change in investment value as percentages from initial investment. It should be noticed that when the trading costs were 3.0% or higher, highest profits with PX 50 were gained with a trading rule that never gave a trading signal. Therefore the trading costs did not affect and the maximum profit equals the profit gained with best secondary investment.

	Primary investment	Highest profit gained with each primary investment (in %)								Highest loss gained with each primary investment (in %)							
		0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5
Hungary	Matav	74.9	37.2	29.1	21.5	14.3	7.5	1.8	-3.3	-68.0	-74.2	-79.6	-87.8	-92.8	-95.7	-97.5	-98.5
	Mol	264.4	250.0	236.2	222.9	210.0	197.6	185.6	174.0	-55.7	-70.0	-83.3	-91.4	-95.6	-97.8	-99.0	-99.6
	Otp	580.1	469.5	402.1	342.4	289.5	242.8	201.4	178.4	-51.1	-71.2	-84.3	-91.4	-96.2	-98.4	-99.3	-99.7
	Richter	925.3	462.9	396.8	351.2	309.6	271.7	237.1	205.6	-54.4	-66.0	-77.9	-85.7	-93.3	-97.6	-99.1	-99.7
	Hu Portfolio	92.5	87.5	82.5	77.7	73.0	68.4	63.9	59.5	-32.4	-45.9	-66.1	-79.6	-88.5	-93.5	-96.3	-97.9
	Bux	1321.5	640.9	342.7	257.9	189.0	152.6	121.0	93.2	-27.4	-54.9	-78.2	-91.4	-96.6	-98.7	-99.5	-99.8
Czech	Cesky	224.2	105.5	29.9	6.8	3.5	1.4	-0.7	-2.7	-58.4	-65.5	-81.4	-91.8	-96.4	-98.4	-99.3	-99.7
	Cez	498.8	412.7	338.5	274.8	220.1	173.2	132.9	98.5	-52.2	-79.7	-93.4	-97.9	-99.3	-99.8	-99.9	-100
	Komercni	649.2	367.7	272.3	243.3	216.4	191.6	168.6	147.2	-58.3	-78.5	-88.9	-95.4	-98.2	-99.3	-99.7	-99.9
	Philip	409.1	316.3	243.7	189.4	143.4	104.5	71.7	63.6	-56.5	-70.6	-85.9	-95.0	-98.4	-99.5	-99.8	-100
	Cz Portfolio	292.7	143.7	86.3	68.9	44.5	37.1	30.1	23.4	-18.1	-51.4	-75.8	-90.2	-96.0	-98.4	-99.4	-99.7
	PX 50	161.4	118.2	87.6	61.1	38.3	18.6	7.3	7.3	-51.2	-73.3	-85.6	-94.1	-97.6	-99.1	-99.6	-99.9
Poland	Tpsa	69.6	47.4	28.0	11.1	-3.7	-16.5	-23.0	-25.4	-63.2	-72.8	-83.1	-89.5	-93.5	-96.0	-97.5	-98.5
	Elektrim	1434.4	1187.5	979.4	876.4	813.9	755.1	699.8	647.9	-94.3	-95.7	-97.3	-98.8	-99.5	-99.8	-99.9	-100
	Kghm	34.0	26.2	18.8	11.8	5.1	2.6	1.6	0.6	-72.6	-84.7	-91.5	-95.3	-97.4	-98.5	-99.2	-99.6
	Pekao	145.1	140.3	135.5	130.7	126.1	121.5	117.0	112.6	-24.0	-46.0	-61.9	-73.1	-83.7	-90.1	-94.0	-96.4
	Prokom	247.8	196.3	152.2	114.5	82.2	54.7	31.2	11.2	-62.9	-64.9	-68.3	-81.7	-89.5	-94.0	-96.6	-98.0
	Pl Portfolio	68.1	32.3	20.0	16.0	12.1	8.4	4.9	1.5	-45.6	-55.5	-67.6	-79.1	-86.7	-91.6	-94.7	-96.7
	Wig	4365.1	2113.4	1045.5	517.6	232.0	161.0	110.3	69.3	-41.4	-59.1	-79.0	-89.4	-95.6	-98.4	-99.4	-99.8
All	Shr Portfolio	54.9	19.8	17.8	16.0	14.1	12.3	10.6	8.8	-14.0	-30.6	-53.6	-70.2	-81.0	-87.9	-92.3	-95.1
	Ind Portfolio	172.7	62.8	30.1	10.0	4.9	2.4	1.2	0.0	-19.6	-49.7	-74.3	-88.4	-94.6	-97.4	-98.7	-99.4
	Sum	4365.1	2113.4	1045.5	876.4	813.9	755.1	699.8	647.9	-94.3	-95.7	-97.3	-98.8	-99.5	-99.8	-99.9	-100

The highest profit statistics would encourage to take the additional risk. For example, technical analysis was able to bring maximum profits of 4365.1% and the figure came down to respective buy & hold strategy profit level of 431% only when one-way trading costs closer to 2% were introduced. On the other hand, the highest loss produced with active trading was 94.3%. The trading costs made the results even worse as in the worst case the 3.5% one-way trading costs caused an active investor to lose almost the whole invested sum.

Now also the profitability of single trades is summarized. In more detail, the investment value before each buy signal is compared to the value before subsequent sell signal and the difference is seen as a profit gained by a single trade. Consequently, the word *trade* is here a bit misleading. The following table shows this short-term profitability together with the total amount of sell decisions done during the simulations.

Table 24 Trade-level trading statistics
The table indicates the quantities of sell signals, average profitability of single trades, relative amount of positive trades and extreme profit figures with different trading costs. A trade means here a sell signal for changing the position from share or index to a secondary investment. Therefore, trade success means the percentual difference between buy and sell values.

	Primary investment	Qty. of sells	Average trade profit								Relative amount of positive trades (in %)								Largest winning trade		Largest losing trade	
			0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	0.0	3.5	0.0	3.5
Hungary	Matav	3360	0.03	0.02	0.00	-0.02	-0.03	-0.05	-0.07	-0.08	41.3	39.4	36.3	33.5	32.3	29.8	28.9	27.0	93.2	86.4	-57.8	-59.2
	Mol	8320	0.04	0.01	-0.03	-0.06	-0.10	-0.13	-0.16	-0.20	34.2	30.1	25.9	24.4	22.0	20.8	19.5	18.8	322.3	307.6	-33.4	-35.8
	Otp	10270	0.17	0.13	0.09	0.05	0.01	-0.03	-0.08	-0.12	41.6	38.2	34.6	31.1	29.4	26.7	25.1	23.1	472.8	452.8	-52.4	-54.1
	Richter	9118	0.30	0.25	0.20	0.15	0.11	0.06	0.01	-0.04	44.0	41.6	39.1	36.2	32.9	30.4	28.0	25.7	512.0	490.6	-70.5	-71.5
	Hu Portfolio	18578	0.03	0.01	-0.01	-0.04	-0.06	-0.08	-0.10	-0.12	37.3	34.2	30.9	28.0	25.6	23.4	21.8	20.3	472.8	452.8	-57.8	-59.3
	Bux	11879	0.43	0.36	0.30	0.24	0.18	0.12	0.06	0.00	49.6	46.1	42.2	39.3	36.6	32.2	28.8	26.9	331.0	315.9	-44.4	-46.3
Czech	Cesky	5157	0.03	0.00	-0.02	-0.05	-0.08	-0.10	-0.13	-0.15	40.6	37.3	34.0	31.1	29.6	27.3	24.3	23.0	100.2	93.2	-56.7	-58.2
	Cez	10924	0.10	0.06	0.02	-0.02	-0.06	-0.10	-0.14	-0.18	37.3	35.0	31.2	29.2	26.7	24.5	23.2	21.7	155.6	146.6	-31.7	-34.1
	Komercni	8919	0.45	0.33	0.29	0.24	0.20	0.15	0.11	0.06	53.3	50.3	45.7	42.8	38.2	36.3	34.4	29.5	280.7	267.4	-56.1	-57.6
	Philip	9561	0.22	0.17	0.11	0.06	0.00	-0.05	-0.10	-0.16	41.9	38.2	32.5	29.7	27.2	25.8	24.0	23.2	142.4	133.9	-36.7	-39.0
	Cz Portfolio	22430	0.11	0.07	0.04	0.02	-0.01	-0.03	-0.06	-0.09	43.1	40.3	35.7	33.2	30.4	28.4	26.4	24.3	280.7	267.4	-56.7	-58.2
	PX 50	7701	0.07	0.04	0.01	-0.02	-0.05	-0.08	-0.11	-0.14	42.3	36.4	29.8	26.1	23.8	22.6	20.2	18.8	88.7	82.1	-24.2	-26.9
Poland	Tpsa	1992	0.00	-0.02	-0.04	-0.05	-0.06	-0.08	-0.09	-0.11	27.8	29.1	25.8	24.5	22.4	20.5	19.2	18.5	105.0	97.9	-50.1	-51.8
	Elektrim	6987	0.56	0.28	0.45	0.42	0.39	0.36	0.33	0.30	40.8	38.1	36.9	34.5	31.5	31.0	30.2	29.2	1927.5	1856.5	-92.2	-92.5
	Kghm	4039	0.00	-0.01	-0.03	-0.04	-0.05	-0.07	-0.08	-0.10	37.2	34.5	32.3	28.8	26.0	22.6	21.7	19.9	82.8	76.4	-42.9	-44.9
	Pekao	3958	0.06	0.04	0.03	0.01	-0.01	-0.02	-0.04	-0.05	44.3	40.3	37.4	33.8	30.0	28.5	27.0	26.3	124.9	117.0	-36.2	-38.4
	Prokom	3355	0.11	0.09	0.08	0.06	0.04	0.02	0.00	-0.02	41.7	39.6	37.9	36.8	35.9	34.3	32.5	32.0	270.6	257.6	-40.4	-42.5
	Pl Portfolio	7958	0.01	0.00	0.00	-0.01	-0.02	-0.03	-0.03	-0.04	37.3	35.4	32.9	30.7	27.7	25.9	24.6	23.8	270.6	257.6	-92.2	-92.5
	Wig	11444	0.50	0.43	0.36	0.30	0.23	0.17	0.10	0.04	44.8	42.3	38.2	34.6	31.5	28.4	25.3	22.7	1770.4	1705.0	-47.6	-49.5
All	Shr Portfolio	47176	0.01	0.00	0.00	-0.01	-0.02	-0.03	-0.04	-0.05	38.6	36.4	32.8	30.3	27.4	25.4	23.8	22.3	270.6	257.6	-92.2	-92.5
	Ind Portfolio	14105	0.05	0.03	0.01	-0.02	-0.04	-0.06	-0.08	-0.10	42.6	39.0	34.3	30.8	28.2	25.3	22.3	20.3	88.7	82.1	-42.2	-44.2
	Sum	227231	0.14	0.10	0.08	0.05	0.02	-0.01	-0.04	-0.07	41.2	38.5	34.7	31.9	29.2	27.0	25.0	23.3	1927.5	1856.5	-92.2	-92.5

On average, each trade profited the investor with 0.14% when the trading costs were ignored. The average was still positive even after 2% one-way trading costs. Given that the previously researched average and even highest emerging market one-way trading costs were lower than 2%, the trading rules did profit the investor, although not necessarily as well as buy & hold strategy. On the other hand, it can be seen that with two shares the average profit was negative as soon as the trading costs were introduced. However, this does not simply mean that trading would have worked worse than buy & hold strategy as the trading rules may have just assisted in cutting the losses.

It can also be seen in the table that the success of all 227 231 trades varies remarkably. An investor may have gained a maximum profit of 1927% by buying the share and selling it according to the trading signals, when the trading costs are ignored. Even after 3.5% one-way trading costs, the profit is 1856.4% as naturally the role of trading costs is not so important when the profitability is evaluated in trade level. Then again, although the trading systems have been designed to cut the losses, they still occur. The highest loss caused by a single trade is as high as 92%. Therefore, based on average and extreme figures, it can be concluded that even a trial use of trading rules can be profitable, but the associated risk is evident.

Finally, as the trading success varies according to different trading environments, an additional interest lies in the possibility to point out possible characteristics that could reveal profit opportunities already in original time series. This final approach is inspired by an idea that there might exist a way to reveal correlation between some time series characteristics and trading statistics.

Previous chapters show how the profitability of active trading depends heavily on the total trading costs that will naturally increase when the amount of trades increases. Therefore, it was also surveyed whether there is regression between the amounts of trades and amounts of abnormal profits. Further, as the amounts of trades depend on time series fluctuations, it was now tested if there is a connection between time series standard deviation and amounts of trades.

All different regressions between abnormal profits, amounts of trades and standard deviations of all original time series were surveyed in all periods, but no significant relationship was found. R squares measuring these regressions were in most of the cases less than 5%. Some peaks occurred, but even the highest figure was less than 17%.

9 CONCLUSIONS

This study provides an approach for testing weak form market efficiency. The methodology replicates general guidelines of previous studies, but simultaneously pays special attention on both previous rationale presented for methodology selection and the consequences of assumptions made during the methodology selection. Further, as the market efficiency has been evaluated based on the usefulness of technical analysis, the study provides also information on theoretical success of technical analysis. Consequently, while the main contribution of the study lies in providing more information on less-researched East European markets, there is additional information that can be considered as "secondary results".

The study results are now summarized according to these four main areas of interest: Methodology selection, East European market efficiency, effects of methodology variations and usefulness of technical analysis.

9.1 Methodology Selection

As the *methodology selection* has a remarkable effect on the market efficiency research results, the selection has caught a lot of attention also in this study. Although previous studies provide various exemplary methodologies, in this study the first 3 chapters provide supporting information on market efficiency and market efficiency testing. This has been used to be able to decide on an appropriate methodology in the following 3 chapters.

Basing on the previous studies and econometric modeling literature, the research data is first tested with statistical tools like runs tests. However, although the statistical methods may reveal forecastable patterns in market data, they are stated to be inadequate for market efficiency evaluation. Market efficiency evaluation requires estimations on possibilities to make abnormal profits. Therefore, the main focus has been in the usefulness of technical analysis.

To be able to decide the actual technical analysis method, the methodologies used in previous studies are discussed and compared to the ones recommended in technical analysis literature. The conclusions are presented in the simple trading rule summary provided in chapter 5. Consequently, the trading rule selection is based on both previous studies and technical analysis literature indicating rules that are most frequently tested and recommended for certain environments.

According to the technical analysis literature, the trading rules differ considerably and therefore optimal trading rule selection requires several "correct" assumptions on the market characteristics. Especially the decision whether the market is assumed to be trending or antitrending is crucial. Trend-following rule should be selected for trending markets while trading-range markets need an oscillator or similar sensitive method forecasting consequences of more horizontal movements. Similarly, single rules and the parameters needed for rule tuning have a considerable impact on rule performance, but here the guidelines differ.

This study tries to maintain a neutral view on the rule selection and to avoid data-snooping. Simultaneously, accepting a random rule selection would underestimate the assumed importance of trending/antitrending market differences. Therefore, one trading strategy recommended for both trending and antitrending markets was to be selected. The actual rule selection was based on common recommendations and methods used in previous studies.

The selected trend-following method, variable length moving average (VMA), has been applied in several studies with various market data. The rule has been used e.g. in the studies by Brock et al. (1992), Bessembinder & Chan (1995 and 1998), Hudson et al. (1996), Ready (1997), Ratner & Leal (1999) and Sullivan et al. (1999). For example, in the Brock et al. study, the method selection has been reasoned further with the idea, that the rule is one of the simplest and most widely used technical trading rules. Also in technical analysis literature this method has been honored for being suitable for clear uptrend or downtrend analysis.

The applied VMA rules were (1,50,B), (1,150,B), (5,150,B), (1,200,B) and (2,200,B). The numbers, indicating the period lengths of simple moving averages used in calculating the trading signals, have remained the same also in several previous studies. However, the trading bands (B) have differed as some studies have suggested that bands greater than 0 decrease the oversensitivity appropriately. Consequently, in this study also the common trading bands of 1% and one standard deviation were applied and the amount of different VMA rules totaled 15.

RSI method has not been researched in the same extent, but in technical analysis literature it has been classified as a suitable method for horizontal movements in a trading-range market pointing out quickly the indications of new up and downtrends. However, the parameter selection has been commented also in previous studies. In this study the buy and sell decisions were based on two most common neutralization levels 70/30 and 80/20. Each of these were applied to RSIs calculated with 5-, 14- and 21-day averages that all represent popular period lengths applied in RSI calculation. Consequently, the RSI method was tried with six different parameter combinations.

Also the strategy combination was used. Some referred literature suggest that sensitive oscillators should be mostly seen as secondary tools to be used together with the trend analysis. Therefore an ideal system is considered to include a combination of an oscillator and a trend-following indicator. In this study the combined rules mean simultaneous use of MA and RSI rules. Consequently, the combination rules give buy and sell decision when both MA and RSI rules agree on this. Each of the previously mentioned fifteen MA rules are tried together with each one of the six RSI rules totaling 90 different combinations.

The selected rules together with the presented trading rule summary and rationale for the rule selection can be considered as the first substance of the study. This can be also seen as a future study methodology recommendation that complements the methodology selection rationales presented in previous studies.

9.2 Evaluation of Market Efficiency

The major contribution of this study lies in the *data selection*. The purpose of this study is to research the market efficiency in Budapest, Prague and Warsaw Stock Exchanges. While similar methods have been applied in several studies, emerging markets and especially these East European markets have been less researched and therefore this study is motivated to employ the methodology to new markets.

According to the statistical time series analysis, the market price development of only three individual stocks was stationary. For autocorrelation evaluation the results were double-checked with residuals and first-order derivated time series. However, even after these appropriate operations there was only one series that did not appear to include significant autocorrelation. Also the runs tests were implemented with residuals and first-order derivations. With eight series out of sixteen the tests suggested that runs did not occur only by chance. Consequently, the autocorrelations and runs test results proposed rejection of random walk for almost all the series.

Harvey (1995b) suggested that the level of autocorrelation is directly associated to the size and the degree of concentration of the market. As the selected markets simultaneously appear as very concentrated and autocorrelated ones, this research supports the theory.

As the abnormal profits mean profits exceeding buy & hold strategy profits, buy & hold strategy profits were now evaluated to indicate the development of complete series. The profits varied heavily, from -94.79% to 945.88%. However, most of the buy & hold profits were more moderate and hence the average technical analysis profitability and rule suitability was not obvious beforehand.

When trading success and market efficiency was finally evaluated, the study concentrated on the amounts of trading simulations producing abnormal profits. Consequently the profit level was not relevant, but the information whether trading was able to produce any abnormal profits. As the research evaluated the success of an average investor, the environments providing abnormal profits in more than 50% of the cases were regarded as indications of possible inefficiencies.

First the general trading results were analyzed. When the trading costs were ignored, active trading brought abnormal profits in 39% of all the simulations. However, the success of technical analysis varied considerably between different shares, indices and portfolios. When the efficiencies of each of the markets were evaluated, the main interest lied in the portfolios and indices reflecting the average market characteristics. The results with established country-specific portfolios varied heavily from 2% of Czech to 78% of Poland. Simultaneously, the profits brought by selected major indices varied more moderately as active trading with PX 50 index brought abnormal profits in least i.e. 36% of the cases while Wig brought abnormal profits in most i.e. 71% of the cases.

Based on these results, at least Polish market might be interpreted as an inefficient one. However, no conclusions should be drawn before the trading costs are introduced. Although already the introduction of 0.5% trading costs affected the results remarkably, more relevant results are provided by figures reflecting the trading success with more realistic trading cost levels. It has been surveyed that average round-trip trading costs in emerging markets have been 1.80% while the highest 3.59% trading costs have been found in Czech markets. Consequently, the main interest lied in the results gained with closest applied 1.0% and 2.0% one-way trading costs.

Now the results indicated that from all primary investments only 3-4 of the selected shares may have been traded profitably. Poland portfolio and Wig index gained abnormal profits in more than 50% of the cases still after lowest applied trading costs, but these figures decreased considerably after 1.0% trading costs were applied.

Consequently, none of the markets could be interpreted as inefficient ones. To avoid data-mining, the conclusions on market efficiency were based on averages, although the following chapter indicates how the further research did discover market inefficiencies with some of the methodology variations.

When the trading results were compared to the results obtained with statistical tools, not too much correspondence was found. The first observation supporting this connection between autocorrelation and market inefficiency was that Pekao, the only series with non-significant autocorrelation, provided almost no abnormal profits and the only profits disappeared when any trading costs were introduced. Simultaneously, the series with highest autocorrelations did produce above-average number of abnormal profits. However, the series providing abnormal profits in as many as 98% of the simulations included autocorrelation just slightly above the significant level. The findings in market efficiency were still similar to the ones presented in previous studies. The rejection of random walk indicated that conditions for successful technical analysis and possible market inefficiencies did exist.

9.3 Effects of Methodology Variations

The research provides also information on how the different *methodology variations* affect the results. All these different argued aspects have often been discussed, but the effects have rarely been demonstrated.

The variations include differentiations of trading rules, trading costs, research periods, secondary investments and performance indicators. Most interesting results are related to different trading costs, already introduced in the previous chapter. Now the other variations and their effects on trading performance and market efficiency evaluation will be discussed.

Trading rule performances varied remarkably. When the average MA, RSI and combination rule profits were compared, the moving averages seemed to be most profitable. After the lowest 0.5% trading costs were applied, the average relative amount of simulations providing abnormal profits with MA rules was 35%, with RSIs 26% and with combination rules 27%.

The performance of particular trading rules naturally depended on applied parameters i.e. the calculation periods, trading bands and neutralization levels that all had a notable effect on trading results. From different RSI neutralization levels, the 70/30 rules seemed to bring the best average results. But when different calculation periods were compared, no clear connection between the results and calculation period lengths was observed. Simultaneously, the combination rule success seemed just to be based on the success of original MA and RSI rules. However, there were several exceptions.

Also trading bands seemed to have a clear effect on trading success. It could be noticed that nearly in all of the cases the band of one standard deviation profited the investor most frequently. Simultaneously, the superiority of bands 1% and 0% varied. Therefore it could be concluded that the risk-adjustment through the use of standard deviation band, recommended also by Ratner & Leal (1999), seems to work.

Trading rule success could also be compared e.g. to Sullivan et al. (1999) study, where the best performing Brock et al. (1992) rule was also the (1,50,B)[25] MA. However, as there are no similar previous studies with East European data, the findings could not be directly compared to other studies.

Also here the main interest, however, lied in the methodology variations actually affecting the evaluation of market efficiency. To demonstrate this, again the cases where abnormal profits had been gained in at least 50% of the simulations were highlighted. These results varied again considerably. There could not be found two basic rules providing equal results even on market efficiency. Different rules gave different indications of market efficiency especially with lower trading costs. With higher costs only few rules produced abnormal profits in more than 50% of the cases. For example, after employing the best performing MA and RSI rules to major indices or the index portfolio, the results indicated all the markets to be inefficient even with trading costs of 0.5% or 1.0%, depending on the rule. Simultaneously, if the evaluation was based on the best performing 21-day 80/20 RSI rule, other markets were revealed as efficient ones when trading costs higher than 1.0% were introduced, but the Polish data indicated inefficiency even with 2.0% trading costs.

Also trading bands changed the evaluation of market efficiency, but only on Poland markets. When the bands of standard deviation and 1% were applied to Wig index, the average results indicated inefficiency. However, the results gained with 0% band were well below 50% and thus indicated the market to be inefficient. The results gained with Poland portfolio behaved similarly, but now the standard deviation was the only band providing abnormal profits in less than 50% of the cases.

Additionally, the methodology variations pointed out that the use of oscillators was not a great help to improve performance. This observation is similar to the one presented by Isakov & Hollistein (1999).

The *secondary investments* didn't change the trading results to a great extent. Naturally 2% fixed rate profited more frequently than 0%, but the difference was not remarkable. However, when index was used as a secondary investment, the profits differed sometimes considerably from the ones gained with fixed rates. At times an investment in index improved the trading success, but usually also the index value had obviously decreased after the applied trading rule had given a sell signal.

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[25] As Sullivan et al. (1999) replicated the Brock et al. (1992) study with same trading bands, in their research the best trading rule employed 1% band.

The effects on market efficiency evaluation were mainly related to Poland markets. When Poland portfolio was used as a primary investment and index as a secondary investment, abnormal profits were gained only rarely, while 2% and 0% interest rates brought abnormal profits in at least 63% of the cases. With Wig the difference was found only when the lowest applied trading costs were involved. Now the only secondary investment providing figures above the 50% limit was 2% interest.

At this point also the differences of *performance indicators* can be discussed. In general, the Sharpe ratios favored the time series re-constructed with technical trading rules, which indicated usually smaller standard deviation and smaller risk. However, this can be interpreted as a consequence of the stable secondary investments with fixed 0 and 2% annual interest rates. Due to the nature of Sharpe ratio calculation, a time series including periods of stable profit naturally provides even higher Sharpe than one with zero profit. Further, when the market index is used as the secondary investment, the Sharpe is often smallest due to higher standard deviation. Although the associated risk level decreased the Sharpes, some profitable shares and indices provided also considerably high Sharpes even when index was used as a secondary investment.

When secondary investment's effect on market efficiency is evaluated with Sharpe measures, the sensitive primary investments were the Bux index, PX 50 index and index portfolio. These provided above 50% figures only when 2% interest was used as a secondary investment.

The quantities of cases producing abnormal profits vary considerably between the *periods*. Most primary investments have brought greatest number of abnormal profits on the shortest period 1. On the other hand the quantities of abnormal Sharpes favor also the longer periods. Already these results don't support the earlier suggestions that markets would have become more efficient.

Naturally also the success of trading rules varied between different periods. MA rules succeeded quite equally between periods 1-3, although the average performance decreased slightly when MA rules were applied to more recent data. However, on period 4 these performed exceptionally well providing abnormal profits in 74% of the cases even with 0.5% trading costs. Conversely, the average performance of RSI and combination rules seemed to improve, when those were applied to more recent data. Yet the superiority between the periods was not so clear.

When the period selection effects on indications of market efficiency are evaluated, no common characteristics for the periods were found. In general, all indices together with Czech and index portfolios gave different indications during different periods. For example, without trading costs, Bux index indicated the market to be inefficient only on periods 2 and 3, but the Sharpe ratios indicated the market to be efficient only on the shortest period. Simultaneously, the Sharpe figures of Czech portfolio indicated inefficiency only on the longer period 2, while the PX 50 index gave figures above 50% on two longest periods. From Polish figures abnormal profits of Wig index indicated the market to be inefficient only on the longest period.

When the results were classified by the trading rules, it could be seen that only few rules gained abnormal profits in more than 50% of the cases. However, on period 4 enough abnormal profits were gained even with 8 rules. The respective figures of abnormal Sharpes were much higher. The period 4 figure even indicated, that a research employing the selected trading rules to complete index data and evaluating the trading results with Sharpe measures would have indicated all the markets to be inefficient. Further, the MA profit figures are interesting. A research applying only Brock et al. (1992) MA rules to complete index data, starting on the day when the indices were published, might have provided results indicating all the markets to be inefficient. The finding is similar to the one presented by Hudson et al. (1996), who found that Brock et al. (1992) trading rules had the ability to predict UK returns if sufficiently long series of the stock indices were considered.

In sum, market efficiency estimation is affected by all of the applied variations. The changing results show that market efficiency studies applying similar methodology should take these variations into account before making conclusions on market efficiencies.

Additionally, when the previous conclusions on development of market efficiency are assessed, the weakening performance of MA rules is here considered as the only evidence of a phenomenon that markets adopt the exploitable inefficiencies. If market participants would have realized MA possibilities in market behavior predicting, the use should have spread to average investors and the decreased abnormal profits could be interpreted as a sign of increased efficiency.

9.4 Usefulness of Applied Methodology

The research provided also additional data on *technical analysis usefulness* and profitability. Although the exact profitability figures are not relevant in market efficiency evaluation, this gives an idea of the possibilities of an investor employing technical analysis.

When trading costs were ignored, the average profit of simulated investments was 29.2%. But a costly environment decreased the trading success and this average quickly from positive to negative. However, this does not simply mean that trading would have worked worse than buy & hold strategy as the trading rules could have just assisted in cutting the losses.

The highest profit statistics would encourage to take the additional risk, although the highest loss produced with active trading was 94.3% even without trading costs. Technical analysis was able to bring maximum profits of 4365.1% and the figure came down to respective buy & hold strategy profit level of 431% only when one-way trading costs closer to 2% were introduced.

Additionally, an average trade profited the investor with 0.14% when the trading costs were ignored. The average was positive even after 2% one-way trading costs. Given that the previously researched average and even highest emerging market one-way trading costs were lower than 2%, the trading rules did profit the investor, although not necessarily as well as buy & hold strategy.

Thus, when the usefulness of technical analysis is concluded from an investor's point of view, the research results may provide some encouraging information. It can be concluded that even a trial use of trading rules can be profitable, although the associated risk is evident. However, an investor should place even more attention to the amount of interpretations, modifications and assumptions needed. Although certain rules do work mechanically, all other considerations including rule selection and trading signal interpretation take investors to other non-mechanical decision-making.

When the applied methodology *usefulness in market efficiency testing* is evaluated, the conclusions of previous studies and this research can be summarized. Firstly, the accuracy of statistical testing can be argued. For example, there exists a huge number of different combinations for evaluating the correlation between past and future price movements. Secondly, the rule and parameter selection affects the research results. Therefore, this kind of research investigating market efficiency with only a selected set of trading rules may naturally be argued to provide results defined only by chance. This is also concluded e.g. by Bessembinder & Chan (1998) who insist that there is little reason to view the test results as indicative of market inefficiencies. Still, they view the evidence, that the simple technical rules do contain forecast power, to be fascinating.

9.5 Suggestions for Future Studies

The artificial trading results were naturally affected by also other implied assumptions and generalizations. The research could have provided different results if

- the autocorrelation research would have included even longer lag times. In this research the longest lag was 25 days.
- the taxes had been included in the study.
- the trading costs would have been on the real level. The exact trading costs depend on the investor, but the average levels would have described well the situation of an average investor in each market.
- less liquid stocks with smaller market capitalization would have been selected in the data. For example Lo & MacKinlay (1988) concluded that the random walk model is generally not consistent with the stochastic behavior of returns, especially for the smaller capitalization stocks. However, here the data selection criteria required the selected shares to represent at least half of the market capitalization or turnover to be able to make conclusions concerning the whole markets. Further, selecting less liquid shares would have lead to data-snooping as the shares were already stated to be non-consistent with random walk.
- intraday trading would have been possible. In this research the trading was based on the previous day's closing prices. However, intraday trading would have required very accurate data and an active trading system.
- trade execution period would have been taken into account. This research assumed the investor to have a possibility to use the money invested in the portfolio immediately after each sell. For example, Ready (1997) using intraday data for the US, found that the Brock et al. (1992) trading rules do not beat a buy & hold strategy due to trading costs and the time it takes to execute the actual trade.
- non-synchronous trading would have been taken into account. If some of the prices don't reflect the latest information, the technical trading rules may not be able to obtain the closing price when the markets open the following day. However, this is very difficult to simulate.
- the systematic trading strategy could have been optimized by applying several methods and selecting only the most profitable ones. Although the wider variety of different rule and parameter combinations might have provided more profitable strategies, this would have increased the workload significantly and finally led to data-snooping.

The evaluation of the consequences of these variables would provide complementing and possibly completely different and more realistic trading results.

Other suggestions for future research include further evaluation of the effects of trading costs. As the major importance of transaction costs has been witnessed in this and several previous studies, an alternative trading methodology could now reflect the effects of trading costs already before providing any trading signals. For example, if the employed trading band took also the trading costs into account, only the really profitable trades would be implemented.

Also replication of Bessembinder & Chan (1995, 1998) studies with East European data would give a more comprehensive view on the East European markets. Exploring the markets with same methodologies, applied earlier to US markets, would provide the possible future researchers simple figures to compare and discuss. Further, while Bessembinder & Chan provided break-even transaction costs for trading rules used in Brock et al. (1992) study, the break-even costs for the rules applied in this study would provide a broader view on East European markets. While the practitioners employing technical trading methods might require the actual share-specific break-even costs in their active trading, already average costs would assist the future researchers.

Additionally, the studies could be extended to define the correlations between market development, sensitivity of trading rules, amounts of trading signals, levels of trading costs and abnormal profits. Naturally the importance of trading costs increases when the amount of trading signals increases, but a further study might bring more information on market characteristics revealing possibilities for profitable trading and possibly also define the criteria for successful use of each rule.

Another suggestion for future research includes the use of a system mentioned in the chapter 5.2 i.e. a third kind of market structure indicator determining whether a market is in a trending or antitrending mode. An exemplary system would be e.g. the trend movement index system. This would be still different from the simultaneous use of complementary trend-following and trading-range rules applied in this study. Third method would be the particular tool indicating the time to switch between these two. On the other hand, addition of a "switching indicator" would make trading system much more complex and bring in several new parameters to be selected and optimized.

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Expected Return Theories

All members of the class of "expected return theories" can, be described notationally as follows:

$$E(\tilde{p}_{j,t+1} \mid \Phi_t) = \lfloor 1 + E(\tilde{r}_{j,t+1} \mid \Phi_t) \rfloor p_{jt},$$

where E is the expected value operator; p_{jt} is the price of sensitivity j at time t; $p_{j,t+1}$ is the price at t+1 (with reinvestment of any intermediate cash income from the security); $r_{j,t+1}$ in the one-period percentage return $(p_{j,t+1}-p_{jt})/p_{jt}$; Φ_t is a general symbol for whatever set of information is assumed to be "fully reflected" in the price at t; and the tildes indicate that $p_{j,t+1}$ and $r_{j,t+1}$ are random variables at t. (Fama 1970)

Fair Game Model

According to Fair game model, it is impossible to establish a trading system based only on information Φ_t bringing expected profits or returns in excess of equilibrium expected profits or return. Thus, let

$$x_{j,t+1} = p_{j,t+1} - E(p_{j,t+1} \mid \Phi_t).$$

Then

$$E(\tilde{x}_{j,t+1} \mid \Phi_t) = 0$$

which, *by definition*, says that the sequence $\{x_{jt}\}$ is a "fair game" with respect to the information sequence $\{\Phi_t\}$. Or, equivalently, let

$$z_{j,t+1} = r_{j,t+1} - E(\tilde{r}_{j,t+1} \mid \Phi_t),$$

then

$$E(\tilde{z}_{j,t+1} \mid \Phi_t) = 0,$$

so that the sequence $\{z_{jt}\}$ is also a "fair game" with respect to the information sequence $\{\Phi\}$.

In economic terms, $x_{j,t+1}$ is the excess market value of security j at time t+1: it is the difference between observed price and the expected value of the price and the expected value of the price that was projected at t on the basis of the information Φ_t. And similarly, $z_{j,t+1}$ is the return at t+1 in excess of the equilibrium expected return projected at t. (Fama 1970)

Random Walk Model

Together the two random walk hypotheses constitute the random walk model. Formally, the model says

$$f\left(r_{j,t+1} \mid \Phi_t\right) = f\left(r_{j,t+1}\right),$$

which is the usual statement that the conditional and marginal probability distributions of an independent random variable are identical. In addition, the density function f must be same for all t. (Fama 1970)

Expression of course says much more than the general expected return model summarized by the equation. For example, if we restrict the expected return model by assuming that the expected return on security j is constant over time, then we have

$$E\left(\tilde{r}_{j,t+1} \mid \Phi_t\right) = E\left(\tilde{r}_{j,t+1}\right).$$

This says that the mean of the distribution of $r_{j,t+1}$ is independent of the information available at t, Φ_t, whereas the random walk model, expressed with the equation, in addition says that the entire distribution is independent of Φ_t. (Fama 1970)

Submartingale model

Suppose we assume in the general expected return model summarized by the equation that for all t and Φ_t

$$E(\widetilde{p}_{j,t+1} \mid \Phi_t) \geq p_{jt},$$

or equivalently,

$$E(\widetilde{r}_{j,t+1} \mid \Phi_t) \geq 0.$$

This is a statement that the price sequence $\{p_{jt}\}$ for security j follows a submartingale with respect to the information sequence $\{\Phi_t\}$. (Fama 1970) The expected price for the next period is above or equals current price p_{jt} due to the information Φ_t.

Martingale model

Suppose we assume in the expected return model summarized by the equation that for all t and Φ_t

$$E(\widetilde{p}_{j,t+1} \mid \Phi_t) = p_{jt},$$

or equivalently,

$$E(\widetilde{r}_{j,t+1} \mid \Phi_t) = 0.$$

This is a statement that the price sequence $\{p_{jt}\}$ for security j follows a martingale with respect to the information sequence $\{\Phi_t\}$. Martingale model is almost similar to the submartingale model. The expected price for the next period only equals current price p_{jt} due to the information Φ_t.

Simple Moving Average

The simple moving average (SMA) can be calculated with the following equation:

$$MA = \sum_{t=T-n}^{T} p_t / n,$$

where T = current time, n = calculation period length and p_t is the price p at time t.

Weighted Moving Average

The weighted moving average (WMA) can be calculated with the following equation:

$$WMA = \sum_{t=T-n}^{T} (w_t p_t) / \sum w_t,$$

where T = current time, n = calculation period length, w_t = the weight assigned for p_t at time t and p_t is the price p at time t.

Exponential Moving Average

The exponential moving average (EMA) can be calculated with the following equation:

$$EMA = (1 - w) EMA_{t-1} + p_t w,$$

where EMA_{t-1} indicates the previous exponential moving average, p_t is the price p at time t and w is a fixed weight that can be calculated with the following equation:

$$w = \frac{2}{1+n},$$

where n is again the length of the average calculation period.

Triangular Moving Average

The triangular moving average (TMA) can be calculated with the same equation as WMA:

$$TMA = \sum_{t=T-n}^{T} (w_t p_t) / \sum w_t,$$

where again T = current time, n = calculation period length and p_t is the price p at time t. While in WMA a higher weight is assigned to the more recent observations, in triangular moving average the majority of the weight is assigned to the middle portion of the data. For example, for a 7 period moving average, the weighting factors could be 1, 2, 3, 4, 3, 2, 1.

Hungary Schedule

Equity Section:

08.30 - 09.00	Opening period for all the securities listed on the market of equities.
09.00 - 09.05	Opening match for all the securities listed on the market of equities
09.05 - 16.30	Period of free trading for all the securities notes listed on the market of equities
09.05 - 16.30	Period of negotiated deals for all the securities listed on the market of equities

Derivative Section / Futures market:

08.30 - 09.00	Opening period of order collecting
09.00 - 09.05	Opening period of order matching
09.05 - 16.30	Free period
09.05 - 16.30	Spread order matching
16.30 - 16.40	Closing period of order collecting
16.40	Closing period of order matching

Derivative Section /Option Market:

08.30 - 09.00	Opening period of order collecting
09.00 - 09.05	Opening period of order matching
09.05 - 16.30	Free period

MMTS Free Market:

08.30 - 09.00	Opening period for all the securities listed on the market of equities
09.00 - 09.05	Opening match for all the securities listed on the market of equities
09.05 - 16.30	Period of free trading for all the securities notes listed on the market of equities
09.05 - 16.30	Period of negotiated deals for all the securities listed on the market of equities

Prague Schedule

17:00 -20:00	Auction regime –closed auction
17:00 -20:00	Block trades
17:00 - 20:00	SPAD – closed phase
07:30 - 09:30	SPAD – closed phase
07:30 - 9:45	Auction regime – closed auction for all securities
07:30 - 16:00	Block trades
09:30	The beginning of computation of continual indices PX 50 and PX-D
09:30 - 16:00	SPAD – open phase
09:45 - 15:45	Continual regime
11:00 - 11:30	Auction for intervention purchases
16:00	Termination of computation of continual indices PX 50 and PX-D
17:00	Publication of the Stock Exchange Price-List (Price Quotations)
17:00 - 20:00	Taking the closing results

Warsaw schedule

Session phases in the single-price auction system:

8:30	Pre-opening: collection of orders for the opening, publication of the IOP (Indicative Opening Price), no transactions.
11:00 and 14:45	Intervention: new orders cannot be placed; the market maker (animator) modifies earlier orders to improve liquidity of a security; if a security does not have a market maker (animator), all market participants may modify their previously-placed orders.
11:15 and 15:00	Auction: determination of the single price and execution of orders.
16:10	Post-auction trading: orders accepted and executed at a price equal to the single price determined in the auction.
16:20	Pre-opening: collection of orders for the next session.

Session phases in the continuous system:

8:30	Pre-opening: collection of market-on-opening orders, publication of the IOP (Indicative Opening Price), no transactions.
9:55	Opening (auction): determination of opening price, execution of orders entered into the system in the pre-opening phase, no new orders.
9:55-16:00	Continuous trading: orders accepted and executed subject to the situation on the market.
16:00	Pre-closing: collection of orders for closing, no transactions.
16:10	Closing (auction): determination of closing price, execution of orders entered into the system in the pre-closing phase.
16:20	Post-auction trading: orders accepted and executed at a price equal to the single price determined in the auction.
16:20	Pre-opening: collection of orders for the next session opening.

Continuous trading - futures contracts:

8:30	Pre-opening: collection of market-on-opening orders, publication of the IOP (Indicative Opening Price), no transactions.
9:00	Opening (auction): determination of opening price, execution of orders entered into the system in the pre-opening phase, no new orders.
9:55-16:00	Continuous trading: orders accepted and executed subject to the situation on the market.
16:00	Pre-closing: collection of orders for closing, no transactions.
16:10	Closing (auction): determination of closing price, execution of orders entered into the system in the pre-closing phase.
16:20	Post-auction trading: orders accepted and executed at a price equal to the single price determined in the auction.
16:20	Pre-opening: collection of orders for the next session opening.

BUX Equity Base

Ranking	Name	% of total capitalization
1	OTP	26.33
2	MAGYAR TÁVKÖZLÉSI RT.	22.05
3	MOL	21.21
4	RICHTER	18.14
5	EGIS	5.07
6	TVK	1.48
7	DÉMÁSZ	1.45
8	DANUBIUS	1.28
9	NABI	0.66
10	RÁBA MAGYAR VAGON RT.	0.65
11	BORSODCHEM	0.52
12	ANTENNA HUNGÁRIA	0.40
13	PANNONPLAST	0.40
14	SYNERGON INFORMATIKAI RT.	0.35

PX 50 Equity Base

Ranking	Name	% of total capitalization
1	KOMERCNÍ BANKA	21.60
2	CESKÝ TELECOM	19.74
3	ERSTE BANK	19.66
4	CEZ	14.97
5	PHILIP MORRIS CR	5.84
6	CESKÁ POJIŠTOVNA	2.22
7	UNIPETROL	1.72
8	JM ENERGETIKA	1.63
9	CESKÉ RADIOKOMUN.	1.60
10	ŽIVNOSTENSKÁ BANKA	1.56
11	SM PLYNÁRENSKÁ	1.19
12	JM PLYNÁRENSKÁ	1.08
13	STC ENERGETICKÁ	0.97
14	SEVEROCESKÉ DOLY	0.89
15	SC ENERGETIKA	0.88
16	MORAVSKÉ NAFT.DOLY	0.80
17	FINOP HOLDING	0.66
18	OKD	0.62
19	SOKOLOVSKÁ UHELNÁ	0.46
20	METROSTAV	0.42
21	PVT	0.42
22	ISPAT NOVÁ HUT	0.27
23	PRAŽSKÉ SLUŽBY	0.19
24	ŽS BRNO	0.16
25	PARAMO	0.11
26	SPOLEK CH.HUT.VÝR.	0.11
27	ŽDAS	0.10
28	ALIACHEM	0.09
29	CESKÁ ZBROJOVKA	0.07

WIG Equity Base

Ranking	Name	% of total capitalization
1	PEKAO	10.23
2	TPSA	9.89
3	PKNORLEN	9.79
4	KGHM	7.24
5	BPHPBK	6.97
6	SWIECIE	4.95
7	PROKOM	4.52
8	AGORA	3.68
9	BZWBK	3.02
10	STOMIL	2.85
11	BIG	2.72
12	INGBSK	2.42
13	°YWIEC	2.37
14	ORBIS	2.09
15	BUDIMEX	2.04
16	BRE	1.96
17	HANDLOWY	1.81
18	DEBICA	1.78
19	COMPLAND	1.58
20	KETY	1.37
21	CERSANIT	1.35
22	KREDYTB	1.08
23	POLIFARBC	0.96
24	JELFA	0.85
25	POLFKUTNO	0.82
26	PGF	0.80
27	SOKOLOW	0.65
28	LPP	0.53
29	SOFTBANK	0.52
30	OKOCIM	0.50
31	ELEKTRIM	0.45
32	FARMACOL	0.44
33	ORFE	0.41
34	GRAJEWO	0.38
35	AMICA	0.37
36	COMARCH	0.37
37	SANOK	0.36
38	ECHO	0.33
39	KROSNO	0.29
40	POLIGR	0.27
41	STERPRO	0.26
42	LENTEX	0.25
43	ELDORADO	0.25
44	ROLIMPEX	0.24
45	NETIA	0.22
46	GROCLIN	0.22
47	TRASTYCHY	0.21
48	RAFAKO	0.20
49	MIESZKO	0.19
50	IRENA	0.18
51	MENNICA	0.18
52	KOGENERA	0.18
53	FORTE	0.16
54	OPTIMUS	0.15
55	MOSTALEXP	0.14

Ranking	Name	% of total capitalization
56	ELBUDOWA	0.14
57	STALPROD	0.13
58	BOS	0.13
59	MOSTALWAR	0.13
60	CSS	0.13
61	JUTRZENKA	0.13
62	APATOR	0.12
63	KRUK	0.12
64	MOSTALSDL	0.12
65	BORYSZEW	0.11
66	GRUPAONET	0.11
67	IMPEXMET	0.10
68	EMAX	0.09
69	STRZELEC	0.08
70	MPECWRO	0.06
71	WILBO	0.05
72	KRUSZWICA	0.05
73	PROSPER	0.04
74	UNIMIL	0.04
75	INDYKPOL	0.03
76	TALEX	0.02
77	BCZ	0.00